POLITECNICO DI MILANO
Master's Degree in Computer Science Engineering
Department of Electronics and Computer Science Engineering

ERACLE
Wearable EMG Gesture Recognition System

AI & R Lab
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To Andrea,
Maria Rosa
and Valentina

Abstract

Eracle is a hand gesture recognition system mainly designed for Human Computer Interaction. It could be employed in Virtual Reality simulations, video games, Augmented Reality environments and Home Automation applications.
It is focused on two different features: EMG signals processing and wearable computer. EMG are biometric signals produced by the muscle during a contraction that are mainly employed in biomedical field for prosthesis control. The whole system has been developed using mobile devices to realize a completely wearable system. In particular, the whole sampling process has been carried out by an acquisition glove worn by the user, while the computing core is fully implemented on Nvidia Tegra 2.
The core of this thesis is the development of the software computing core of Eracle system, while the acquisition glove and the EMG Board (that provides analog to digital conversion of the sampled signal) have been realized in previous works.
The aim of the project is to develop a wearable recognition system based on EMG signals that is able to recognize at least four different hand gestures. The performed tests have shown that Eracle can correctly identify up to five movements with a performance of about 90%. The achieved results are very interesting for such kind of HCI application, that could be effectively employed in daily life computer interaction, making it easier and more immersive.

Sommario

Questa tesi documenta la realizzazione di un sistema per il riconoscimento dei movimenti della mano. Il nome del progetto è "Eracle", poichè il riconoscimento avviene grazie all'analisi dei segnali elettromiografici (EMG) emessi dai muscoli dell'avambraccio dell'utente. Lo scopo consiste nel realizzare un sistema indossabile che possa essere facilmente utilizzato per interagire con un'apparecchiatura informatica. Le applicazioni di questo dispositivo sono molteplici e spaziano dalle simulazioni di Realtà Virtuale, ai videogiochi, alla Realtà Aumentata fino a domotica.

Il progetto Eracle è focalizzato su due aspetti principali: i segnali elettromiografici e i dispositivi indossabili. I segnali EMG sono largamente utilizzati in campo biomedico per il controllo delle protesi, soprattutto per quanto riguarda i pazienti amputati a livello della mano. Inoltre, l'analisi di questo tipo di segnali è utile per la diagnosi di lesioni ai muscoli o ai nervi.
Il secondo punto focale della tesi è costituito dai dispositivi indossabili, ovvero le apparecchiature caratterizzate da dimensioni tanto ridotte da poter essere agevolmente indossate da un utente nelle attività della vita quotidiana. L'uso di questo tipo di dispositivi semplifica alcune attività tipicamente compiute dall'uomo (nel nostro caso, l'interazione con un computer) oppure estende le capacità sensoriali dell'utente.

Eracle è composto fondamentalmente da due unità: il guanto di acquisizione e il modulo di elaborazione del segnale. Il primo è stato sviluppato dall' Ing. Paolo Belluco in precedenti progetti e consiste in un guanto di materiale elastico indossato dall'utente sull'avambraccio. All'intero del guanto sono presenti gli elettrodi che rilevano il segnale elettromiografico emesso dai muscoli e la scheda di acquisizione (EMG

Board) che fornisce la conversione analogico-digitale degli EMG. I segnali di input vengono campionati da tre diversi canali in modalità differenziale.
L'unità di calcolo è stata implementata sulla piattaforma Nvidia Tegra 2. I vari moduli software che provvedono all'elaborazione del segnale, al filtraggio e al riconoscimento del movimento sono stati completamente sviluppati all'interno di questo progetto. Alcune strutture matematiche (matrici, vettori), l'algoritmo di filtraggio FastICA e la Rete Neurale utilizzata dal sistema di riconoscimento sono state fornite dalla libreria open-source LTIlib. L'intero codice sorgente è stato ricompilato ed adattato per l'architettura ARM Cortex-A9 del processore Tegra.

I risultati sperimentali mostrano che Eracle è in grado di distinguere fra cinque movimenti differenti con una percentuale di successo media del 90%. I cinque movimenti utilizzati per la fase di test sono:

- **chiusura della mano;**
- **estensione del polso;**
- **flessione del polso;**
- **apertura della mano;**
- **"click":** questo gesto simula il click di selezione di un mouse; viene eseguito appoggiando il polpastrello dell'indice su quello del pollice ed esercitando una leggera pressione.

Durante lo sviluppo del progetto ci siamo focalizzati principalmente sulla precisione di Eracle nell'identificare correttamente il gesto compiuto e sulle proprietà di ripetibilità del sistema.
Quest'ultimo aspetto è essenziale, poichè solitamente la fase di addestramento e di utilizzo del riconoscitore avvegono in tempi differenti, durante i quali l'utente toglie il guanto di acquisizione.
Tutti i moduli software sviluppati sulla piattaforma Tegra sono stati realizzati appositamente per essere il più possibile indipendenti gli uni dagli altri. Questa scelta è ottima per quanto riguarda la fase di debug - poichè è possibile monitorare i risultati ottenuti da ogni modulo - tuttavia porta ad un aumento del tempo di riconoscimento del gesto principalmente dovuto al numero di operazioni di I/O su file.
Per questi motivi, il principale sviluppo futuro di questo progetto consisterà nel ridurre il tempo necessario al riconoscimento diminuendo il

numero dei campioni analizzati in fase di elaborazione e introducendo alcune ottimizzazioni legate alla scrittura e lettura dei file. Crediamo che, grazie a tali modifiche, sarà possibile migliorare drasticamente il tempo di riconoscimento; inoltre, qualora le prestazioni raggiungessero un livello real-time, sarà possibile applicare Eracle in un contesto industriale per il controllo di manipolatori robotici.

Stato dell'arte dei dispositivi mobili per riconoscimento del gesto

Come specificato in precedenza, questa tesi è focalizzata su due temi: i segnali elettromiografici utilizzati per il riconoscimento del movimento e i dispositivi indossabili. Prima di delineare le tecniche utilizzate nello sviluppo di questo progetto e l'effettiva realizzazione del sistema Eracle è necessario descrivere l'attuale stato dell'arte di entrambi gli aspetti chiave della tesi.
Il riconoscimento del movimento può essere effettuato con molteplici tecniche:

- **Sistemi inerziali** come accelerometri o giroscopi, che forniscono posizione e orientamento dell'oggetto controllato.
- **Segnali biometrici** ovvero tutti quelli generati dal corpo umano. Questa classe include i segnali EMG utilizzati nel progetto, ma anche gli EEG e gli EOG. La scelta degli EMG non è casuale, ma è motivata prima di tutto dai numerosi esempi di applicazione di questa tecnlogia al riconoscimento del movimento e dalla loro facilità di acquisizione rispetto a tecniche quali l' elettroencefalografia.
- **Sistemi basati su analisi dell'immagine:** questa classe comprende tutti i sistemi che utilizzano metodi di estrazione di primitive da immagini per identificare il movimento dell'utente. Mediante questa classe di dispositivi è possibile identificare un gran numero di gesti (solitamente almeno dieci), tuttavia essi richiedono apparecchiature costose e di dimensioni tali da non poter essere considerate indossabili.

I dispositivi indossabili appartengono fondamentalmente a due categorie: i PIC o le piattaforme SoC realizzate per Netbook e Smartphone (fra cui il processore Tegra). I primi sono caratterizzati da un basso costo e da una considerevole difficoltà di programmazione, mentre i

secondi sono programmabili solitamente con linguaggi di alto livello (C++ nel caso del Tegra), ma hanno un costo piuttosto elevato. Inoltre, molti SoC (come il processore Tegra da noi utilizzato) non sono disponibili sul mercato commerciale italiano, ma sono destinati solo ad alcuni partner per sviluppi sperimentali.
E' possibile distinguere i dispositivi indossabili anche in base al loro Sistema Operativo, i due maggiormente utilizzati sono la piattaforma open-source **Android** e quella di Microsoft **Windows CE** (utilizzata nel progetto Eracle). Recentemente, Microsoft ha rilasciato l'innovativo sistema **Windows Phone 7** che dovrebbe semplificare la fase di sviluppo e l'eventuale porting del codice sui dispositivi mobili.

Piano generale e descrizione del progetto
Lo scopo del progetto è realizzare un riconoscitore del movimento basato sull'elaborazione del segnale elettromiografico. Nonostante l' utilizzo degli EMG il principale campo di applicazione di Eracle non è quello del controllo delle protesi, ma quello della Human Computer Interaction. Eracle potrebbe essere impiegato in simulazioni inerenti la Realtà Virtuale o aumentata, nonchè in campi innovativi quali la domotica. Le differenze fra Eracle e le precedenti implementazioni di riconoscitori basati su EMG sono principalmente due:

- **l'utente finale,** contrariamente ad altri progetti realizzati elaborando il segnale elettromiografico per pilotare una protesi, Eracle può essere utilizzato da qualunque persona senza che sia necessario un'intensa e specifica fase di addestramento;

- **l'hardware utilizzato,** che è completamente indossabile, grazie al peso ridotto e alle dimensioni minime.

Independent Component Analysis
Questo algoritmo viene utilizzato fondamentalmente per ridurre il rumore sui segnali acquisiti e per eliminare il crosstalking. Quest'ultimo è un fenomeno tipico legato ai segnali elettromiografici che si verifica perchè ogni movimento compiuto dalla mano è il risultato della contrazione simultanea di più muscoli; per cui il segnale rilevato dagli elettrodi è una combinazione dei segnali originariamente generati. In campo medico questo problema viene superato utilizzando degli elettrodi ad ago, che tuttavia non possono essere impiegati in un' applicazione di HCI.

Poichè ICA fa parte della classe di algoritmi detta Blind Source Separation (BSS) è in grado di separare e isolare i segnali originali. ICA è stato applicato all'analisi dei segnali biometrici solo in tempi recenti.

Dispositivi hardware
I dispositivi utilizzati per la realizzazione del progetto Eracle sono fondamentalmente due: la scheda EMG (EMG Board) e il Devkit Nvidia Tegra 2.
Il primo si occupa della conversione analogico-digitale del segnale EMG acquisito mediante tre canali differenziali. Il processo di conversione è affidato ad un PIC16F688 Microchip.
Nvidia Tegra 2 è un *System on Chip* appositamente realizzato per piattaforme mobili quali Netbook e Smarthphone. Il sistema viene gestito da Windows CE Embedded 6, che fornisce alcune potenzialità di un Sistema Operativo di un PC su una piattaforma di dimensioni ridotte. Il dispositivo è stato interamente programmato in C++ utilizzando direttamente Visual Studio 2008 e le apposite SDK rilasciate da Microsoft.
I due elementi hardware sono connessi via USB grazie ai driver FTDI.

Sviluppo del progetto
Questa tesi è principalmente orientata alla realizzazione dei moduli software per l'elaborazione del segnale elettromiografico campionato mediante il guanto di acquisizione.
Tutti i moduli sono stati implementati *"from scratch"* sulla piattaforma Tegra e consistono fondamentalmente in:

- **serial port manager:** che gestisce la comunicazione dei dati fra l'EMG board e il Tegra;
- **parser:** i dati di input vengono divisi su tre file diversi, ognuno contenente un numero prefissato di campioni;
- **FastICA:** che provvede al filtraggio dei segnali, alla separazione delle sorgenti e all'eliminazione (almeno parziale) del crosstalking;
- **RMS:** questo modulo calcola il Root Mean Square di ogni canale per ogni gesto acquisito;
- **NN Trainer:** questa unità addestra la Rete Neurale con i valori di RMS calcolati nella sezione precedente;

- **NN Recognizer:** l'ultimo modulo del progetto permette il riconoscimento del movimento eseguito dall'utente mediante l' utilizzo della Rete Neurale precedentemente addestrata.

Alcune strutture matematiche (matrici, vettori), l'algoritmo di filtraggio FastICA e la Rete Neurale utilizzata nel progetto sono state fornite dalla libreria open-source LTIlib che è stata adattata all'architettura del processore ARM Cortex-A9 presente sul Devkit Tegra.

Test

I test eseguiti hanno come scopo principale quello di identificare e migliorare l'accuratezza del sistema in fase di riconoscimento.
Eracle ha dato prova di riconoscere correttamente fino a cinque gesti differenti con una performance media del 90%.
Inoltre, alcuni esperimenti sono stati compiuti con successo su un altro soggetto estraneo al progetto, al fine di testare la robustezza di Eracle e l'effettiva facilità di utilizzo.

Conclusioni e sviluppi futuri

Eracle può essere utilizzato per migliorare l'interazione nei videogiochi, nelle simulazioni di Realtà Virtuale o Aumentata, nonchè nel campo della domotica.
É possibile, tuttavia, introdurre numerosi miglioramenti al sistema. Fra questi il principale riguarda la velocità di computazione che può essere - a nostro parere - ridotta a circa la metà del valore attuale mediante opportuni accorgimenti ed ottimizzazioni legati al numero di campioni acquisiti e all'entità delle operazioni di I/O eseguite dai moduli di elaborazione.
Inoltre, viste le buone performance del sistema, crediamo sia possibile estendere il numero di movimenti riconosciuti.
Sarebbe interessante introdurre, accanto a FastICA, alcuni algoritmi di estrazione di features ampiamente utilizzati nell'analisi del segnale, come ad esempio le Wavelet, per migliorare ulteriormente le prestazioni in fase di riconoscimento.
Infine, il sistema Eracle potrebbe essere collegato ad altre periferiche (anche mediante dispositivi wireless) quali ad esempio caschi o dispositivi aptici, per rendere sempre più immersiva e coinvolgente l'interazione con l'ambiente virtuale.

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Contents

Chapter 1

Introduction

"Space: the final frontier. These are the voyages of the starship Enterprise. Its five-year mission: to explore strange new worlds, to seek out new life and new civilizations, to boldly go where no man has gone before."

Star Trek - The Original Series

This thesis describes a gesture recognition system mainly designed for Human Computer Interaction. We have named the whole system "Eracle" since it identifies the user's gestures analyzing the EMG signals generated by a muscle during a contraction. These signals are sampled with surface EMG electrodes placed on the user's forearm. The whole signal processing units of Eracle have been developed on Nvidia Tegra 2, a mobile *System on Chip* that ensures high computing performance in small size.
Once the signals have been sampled by the surface electrodes, they are converted to digital values by the EMG Board. This board is connected to Nvidia Tegra 2 that is the computing core of the system. The acquired samples are filtered with FastICA algorithm, which is a Blind Source Separation method mainly employed in sound engineering and image processing to separate overlapped signals.
Root Mean Square is computed for each input channel for every gesture repetitions; afterwards, these values are employed to train a Neural Network that will classify the movements performed by the user.
When the Neural Network has been trained, the user performs a single gesture that will be identified by Eracle. The main aim of this project is to develop a wearable system that is able to identify at least four different hand gestures performed by the user.

EMG-based movement recognizers are mainly employed in biomedical field to control prosthesis. Instead, Eracle is designed for Virtual Reality applications like video games or Augmented Reality environments. It could also be used in home automation field to control some appliances like the air-conditioner or simply for turning the light on and off. The performed tests show that Eracle is able to recognize at least five different gestures with an average performance about 90%.

Interact with a gesture is simpler and more natural than using devices like keyboard or game controllers. Benko et al in [25], demonstrated that movement recognition can expand the "vocabulary" of HCI devices, thus new features can be added to the controlled appliance.
Wearable devices and EMG signals are the keywords of Eracle project. This system is based on *EMG signals,* but there are many other different techniques to identify movements, for example: inertial navigation system, EEG, EOG and image processing algorithms. Projects about gestures recognition systems mainly employ EMG signals as input data (e.g. muCIs project by Microsoft Research [47, 48]) or image processing techniques (e.g. project Natal/Kinect by Microsoft [18]). The advantage of employing EMG signals for gesture recognition is that they can be sampled with an acquisition glove placed on user's forearm. Thinking about home automation fields, there is no need to install cameras or computer vision appliances in every room.
Eracle is also *a wearable system,* thus it is fully implemented on mobile devices and no desktop PC interaction is necessary to use it. Moreover, such kind of system does not hinder the user's movements, thus, gestures can be performed in a very natural way.
The software running on Nvidia Tegra 2 has been fully written in C++ and has been developed from scratch; however some mathematical features have been provided by LTIlib, a C++ library with data structures and algorithms frequently employed in image processing. This library is open source and has been developed by Aachen University of Technology [13]. Since the target machine of this library is different from the ARM Cortex-A9 architecture of Nvidia Tegra 2, this library has been fully ported and recompiled.
Another main feature of Eracle project is FastICA algorithm, that is a Blind Source Separation method. Its employment for EMG signal filtering has been proposed by Naik et al in [43], [42] and [41]. How-

ever, in the cited implementations, training and recognizing stage are performed offline on the same set of data. In In Eracle system these two steps take place in different times, and they are handled by two different executable files running on Tegra. The employment of ICA methods in handling EMG signals is a novelty, as feature extraction algorithms such as Wavelet or Fourier Transform (STFT) have been usually employed in this field.
The EMG Board - that provides the analog to digital conversion of the sampled data - and the acquisition glove - that includes the EMG Board and the surface EMG electrodes - have been previously developed by P. Belluco.
We have succeeded in realizing a wearable gesture recognizer that achieves a good performance; however, the system could be widely improved. The main future development concerns the reduction of the computational speed of the recognition stage; if we would reach a real-time performance Eracle could also be employed in an industrial context to control a robotic arm. Moreover, we think that this system could recognize more than five gestures with good accuracy.
Finally, it would be interesting to connect Eracle to other devices through a wireless connection, in order to obtain a fully wearable and mobile interaction system.

This thesis is divided into eight different chapters. *Chapter 2* provides an overview about the mobile devices mainly employed in HCI. Moreover, it describes the basic techniques employed for gesture recognition tasks. Such methods are divided into three classes: inertial navigation, biometric signals and image analysis. Mobile devices are described both as hardware solutions and employed OS. *Chapter 3* introduces Eracle and describes the main project's goals. This chapter also provides some reasons of our choices concerning EMG and mobile devices. The last section introduces the general architecture of the project.*Chapter 4* provides some basic principles about Independent Component Analysis, that is the class of algorithm employed for EMG data filtering. This chapter also discusses the main problems we've encountered in employing ICA for processing this kind of signals. *Chapter 5* is focused on hardware devices employed in this projects. It describes both the computing core of Eracle system (Nvidia Tegra 2) and the EMG board that provides analog to digital conversion of biometric signals. *Chapter 6*

provides a detailed description of the whole system. It is focused both on the sampling units - implemented on the acquisition glove - and on the processing modules that are fully developed on Tegra Devkit. In *Chapter 7* some tests results have been discussed, outlining the difficulties that we've encountered and the results obtained following the proposed solutions. Finally, *Chapter 8* summarizes the project's final considerations and describes some possible future developments.
The two appendixes provide the complete code listings of the computing core (*Appendix A*) and some basic principles about EMG signals (*Appendix B*).

Chapter 2

Mobile devices for gesture recognition: the state of the art

"Scott: Computer... Computer? Ah... Hello, computer.
Dr. Nichols: Just use the keyboard...
Scotty: A keyboard, how quaint!"

Star Trek IV - The Voyage Home

This chapter provides the state of the art of the two main subjects involved in this project: gesture recognition and mobile devices. The first section describes the main techniques employed in movement recognition, highlighting that biometrics signals - mainly used for prosthesis control - could be useful adopted in HCI.
In the second section an introduction to mobile device technology is provided, focusing both on hardware and software aspects.

2.1 Gesture recognition

Gesture recognition technology is mainly employed in prosthesis control, but gesture is a basic and simple way to interact among people, and it could be one of the best way to interact with a machine.
Today the main part of HCI is held by visual interaction through a monitor, but interact with a device through gesture could be much easier. Think about the difference between using a mouse instead of a keyboard, or using a drawing tablet rather than an "usual" graphic

program; or consider the success of Nintendo Wii, that is the first game console which uses movement interaction controller.
There are mainly three ways to extract movement information for a gesture recognition application:

- inertial navigation methods;
- biometric signals;
- image analysis.

This section provides an overview of the main methods employed in each mentioned approach.

2.1.1 Inertial navigation methods for gesture and movement recognition

First class of gesture recognition methods is based on inertial navigation techniques that use gyroscopes and accelerometers to measure the rate of rotation and acceleration of the object.

Gyroscopes

Mechanical gyroscopes rely on the principle of the conservation of the angular momentum, which is the tendency of a rotating object to keep rotating at the same angular speed ω about the same axis of rotation in the absence of an external torque. The angular momentum L of an

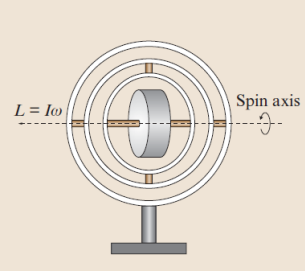


Figure 2.1: Schema of a mechanical gyroscope

object with moment of inertia I rotating at an angular speed ω is given by:

$$L = I \times \omega \tag{2.1}$$

Consider a rapidly spinning wheel mounted on a shaft so that it is free to change its axis of rotation as shown in figure 2.1, if we assume that there's no friction due to air resistance, the rotor axis will remain constant regardless of the motion of the external cage. Rate gyros (RGs) measure the vehicle's rotation rate (angular rate of rotation), integrating them will produce an estimate of the absolute angular displacement of the object.
Gesture recognition devices use special gyroscopes named MEMS (Micro Electro Mechanical Systems), which are based on vibrating mechanical elements to sense rotation. Vibratory gyroscopes rely on transfer of energy between vibratory modes based on Coriolis acceleration. Coriolis acceleration is the apparent acceleration that arises in a rotating frame of reference.
An object moving in a straight line with local velocity v in a frame rotating at a rate Ω relative to an inertial frame will experience a Coriolis acceleration a such that:

$$a = 2v \times \Omega \tag{2.2}$$

Acceleration can be retrieved from MEMS gyroscopes by inducing some local linear velocity and measuring the resultant Coriolis forces. Early MEMS gyroscopes utilized vibrating quartz crystals to generate the necessary linear motion. More recent designs have replaced the vibrating quartz crystals with silicon-based vibrators.
There are three main classes of MEMS gyroscopes:

- Tuning-fork gyroscopes
- Vibrating wheel gyroscopes
- Wine-glass resonator gyroscopes

The main advantages of MEMS gyroscope are that they haven't rotating parts, they have a low-power consumption and they are very small [49].

Accelerometers

Accelerometers are inertial sensors that can be used to measure external forces acting on an object, and to transduce them into a computer-readable signal.
The mechanical accelerometer is essentially a spring-mass-damper system as shown in figure 2.2; when some force is applied it acts on the

mass and displaces the spring, according to the equation:

$$F_{applied} = F_{inertial} + F_{damping} + F_{spring} = m\ddot{x} + c\dot{x} + kx \tag{2.3}$$

where c is the damping coefficient and k the spring's elastic coefficient.
The main drawback of mechanical accelerometers is due to the non

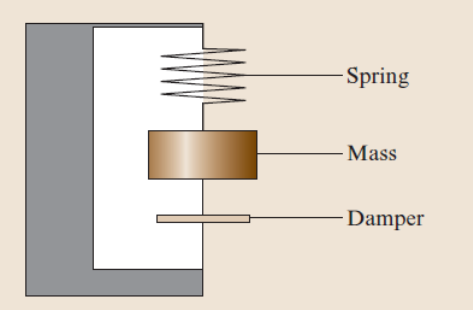


Figure 2.2: Schema of a mechanical accelerometer

ideal performance of the spring; another issue is that this kind of device is particularly sensitive to vibrations.
Another class of accelerometers is based on piezoelectric materials, such as certain crystals across which a voltage is generated when they are stressed, a schema of such device is shown in figure 2.3. A small mass is positioned so that it is only supported by the crystal. When forces cause the mass to act upon the crystal, this induces a voltage that can be measured [49].

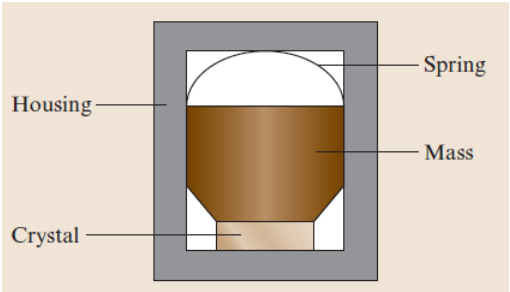


Figure 2.3: Schema of a piezoelectric accelerometer

IMU

An Inertial Measurement Unit (IMU) is a device that utilizes measurement systems such as gyroscopes and accelerometers to estimate the relative position, velocity and acceleration of an object in motion.
An IMU system provides a 6 DoF estimate of the pose: 3 for position (x-y-z axis) and 3 for orientation (usually roll-pitch-yaw frame); commercial IMUs also maintain estimates of velocity and acceleration.
The basic computational tasks of IMU are shown in figure 2.4: the

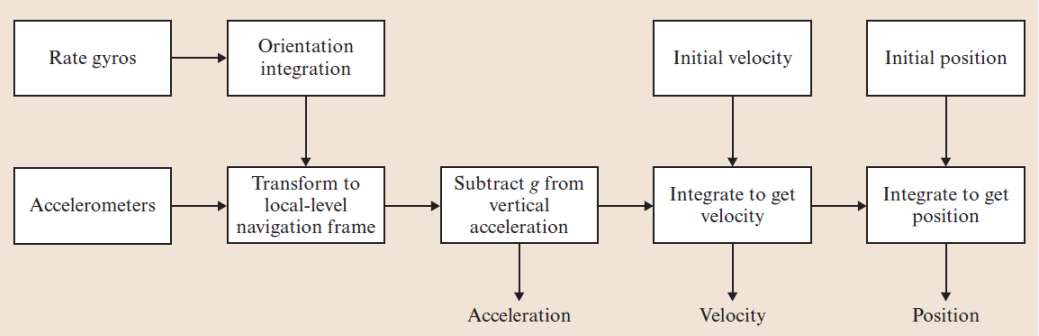


Figure 2.4: Schema of an IMU

gyroscopes data is integrated to provide an ongoing estimate of orientation, at the same time data from accelerometers is used to estimate the instantaneous acceleration of the object. In order to obtain a correct measurement the data acquired have to be rectified with the estimated gravity vector. Velocity and position can be achieved integrating acceleration once or twice respectively.
IMUs are really sensitive to measurement errors in the underline gyroscopes and accelerometers. Drifts in the gyroscopes leads to errors in vehicle orientation relative to gravity, this leads to a wrong computation of the gravity vector. Besides, as the accelerometer data is integrated twice, any residual gravity vector will result in a quadratic error in position. Given a sufficiently long period of operation all IMUs are eventually drift and reference to some external measurements is required to correct this [49].

A successful commercial case: Nintendo Wii

Wii console is an example of what gesture interaction means: first of all the ease of use, but also involvement and user-friendly interaction.

Gesture recognition is performed tanks to the Wii primary controller, which has been realized in several different hardware configurations. There are different Wii controllers, everyone with different specifications, but, generally speaking, Wii controllers for gesture recognition consist of:

- **accelerometer:** ADXL300 or STMicroelectronics LIS3L02AL which measure external forces applied on the controller;
- **infrared optical sensor:** allowing the console to determine where the Wii Remote is pointing;
- **gyroscope:** a MEMS tuning-fork gyroscope, which support the accelerometer and infrared optical sensor capabilities of Wii.

2.1.2 Biometrics signals for gesture recognition

Gesture recognition can be achieved processing biometrics signals produced by a human body performing a movement. There are various biometrics signals that are useful for gesture recognition, they can be summarized in three main classes:

- EOG (Electrooculography signals)
- EEG (Electroencephalographic signals)
- EMG (Electromyography signals)

This subsection describes the main projects carried out with these technologies, especially focusing on EMG signals employment as this is the kind of signals uses in Eracle project.

EOG

Electrooculography (EOG) is a technique for measuring the resting potential of the retina. The main applications are in ophthalmological diagnosis and in recording eye movements. Since eye movements can be tracked by modern technology with great speed and precision, they can be used as a powerful input device, and have many practical applications in HCI [38]. EOG is one of the very few methods for recording eye movements that does not require a direct attachment to the eye itself.

Compared with EEG (see next subsection) EOG has a higher ampli-

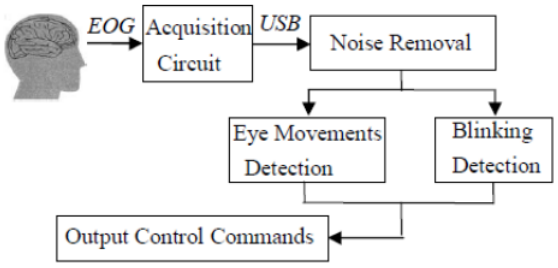


Figure 2.5: Architecture of a EOG-based HCI system

tude, and the waveform is easier to detect. There are also some drawbacks in the employment of this kind of signals: first of all the crosstalk due to the facial muscles activity, secondly the noise produced by head movements [24]. A schema of a typical HCI System based on EOG is shown in figure 2.5.

EEG

An EEG signal is obtained directly through electrodes placed on the scalp, it is a measurement of currents that flow during synaptic excitations of the dendrites of neurons in the cerebral cortex. In fact neurons communicate by means of electrical impulses and generate bioelectromagnetic fields, that can be measured and analyzed in order to detect a pattern corresponding to a movement [34].
One of the most studied movements in EEG field is eye blink that can be employed as a mouse click in a HCI application. Eye blink is easily detected monitoring the signals of the prefrontal lobe because it has a fixed pattern: a downward peak in the negative amplitude region shows an eyes-open event, and then a positive peak shows an eyes-close event; besides the amplitude of these peaks is higher compared to the normal brain activity noticed with an EEG analysis.
A typical eye blink pattern is shown in figure 2.6.
Usually, the EEG signals acquired from the scalp are used to train an Artificial Neural Network to perform a classification of the amplitude pattern in order to recognize the movement executed by the user [28].
EEG technology is mainly applied in medical field, however some studies have been carried out in non-medical applications. [35].

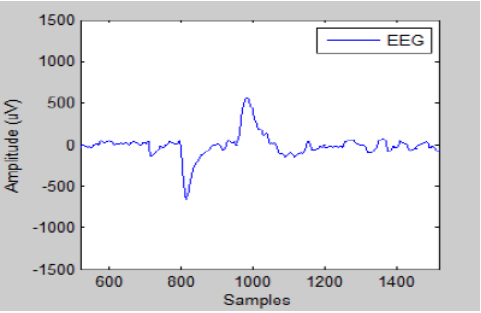


Figure 2.6: Eye blink EEG amplitude pattern

Among various brain signal acquisition methods, the EEG is of particular interest to the BCI community. Brain Computer Interface (BCI) is an emergent multidisciplinary technology that allows brain to control a computer directly, without relying on normal neuromuscular pathways. This technology is mainly employed with paralyzed people who are suffering from severe neuromuscular disorders, as BCI potentially provides them with communication, control, or rehabilitation tools to help compensate or restore their lost abilities [24]. The main drawback of EEG is that they're often contaminated by the artifacts, that are both generated by body movement (internal artifacts) and by 50/60 Hz power supply interference or electrical noise from appliances' components (external artifacts). Besides, electrodes application is uncomfortable and sometimes invasive.

EMG

An EMG signal is produced by a skeletal muscle during a contraction; it could be acquired with an electromyography as a differential signal between a ground and a sensor electrode. Placing electrodes on different location it is possible to identify the movement performed by the end-user just by evaluating the voltage acquired with the electromyography. This method implies a good knowledge of human anatomy, in order to place electrodes correctly.
EMG feasibility in HCI for muscle-computer interface has been widely demonstrated by Saponas et al. [46] in 2008. They were able to differentiate position and pressure of the finger presses, as well as classify tapping and lifting gestures across all five fingers.
The main disadvantage of this method is crosstalking. A movement is

not the result of a single muscle's contraction, but the consequence of a set of muscles working together; it entails that a single muscular fiber takes part in more than just one movement making difficult the gesture distinction task. The crosstalk problem is more significant when the muscle activation is relatively weak, because the differential signal obtained is very low; at a low level of contraction, a precise muscular activity is hardly discernible from background activity [24]. Besides, the EMG signal due to muscle contraction is not locally limited, but it spreads the MUAP activation among the nearest muscular fibers.
The main application field of EMG is the medical one: with an EMG analysis it could be possible to identify some muscular injury.
During the last few years EMG signals have become one of the most promising and useful way to control prosthesis, especially for the limbs amputation. Referring to this last field of application, it is important to define the taxonomy of the movements that can be performed with prosthesis. For grasps actions, the most widely-used taxonomy is the one proposed in 1989 by Cutkosky [30], that is based on function approach. As shown in figure 2.7, Cutkosky identifies 16 different types of grasps: observing the schema from left to right the grasps become less powerful but more precise and the handled objects become smaller. Usually upper limb prosthesis can't replicate all the grasps described by Cutkosky, but only some configurations, such as:

- *the key grip:* is the grasp to handle a key or a CD, this is the configuration number 16 in Cutkosky taxonomy, with the thumb closes down onto the side of the index finger;
- *the power grip:* it employed for grasping a cup or a bag, it is a full-wrap grip that involves all fingers and the thumb;
- *the precision grip:* it corresponds to the number 9 in Cutkosky taxonomy and it is employed to handle small objects in a precise way;
- *the tripod grip:* formed by thumb, index and middle fingers as described in grasp 14 in Cutkosky taxonomy;
- *platform:* the hand is open to hold something (like a plate) on the palm, it is depicted in grasp 15 of Cutkosky taxonomy;
- *index point:* only the finger is extended to point at something, or to use a keyboard.

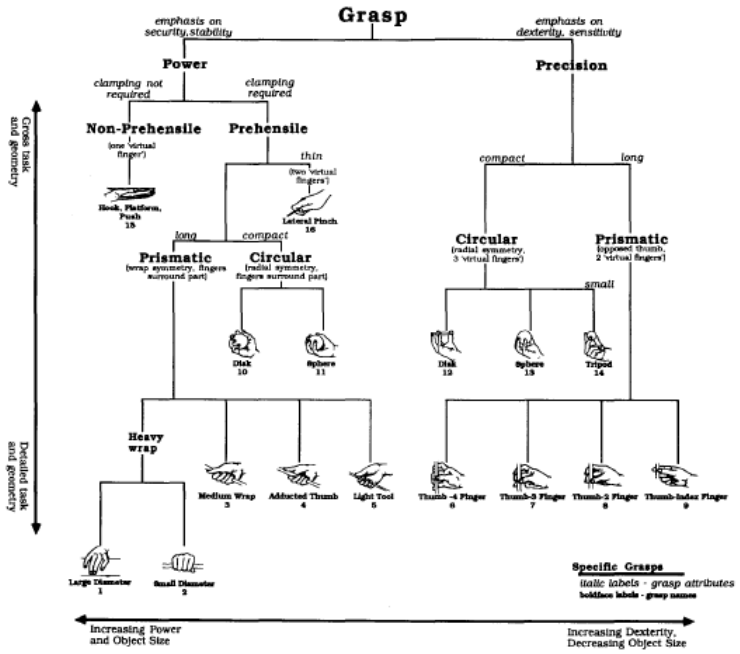


Figure 2.7: The grasps taxonomy proposed by Cutkosky

These configurations are combined to obtain the movements that can be performed by prosthesis; the most widely-used devices can usually perform the following tasks:

- hand closing;
- hand opening;
- wrist extension;
- wrist flexion;
- thumb abduction;
- thumb opposition;
- index extension.

In order to be applied to HCI, EMG technology has to be fitted to non-medical needs: mainly a user will not have time or expertise to adjust a complicated appliance just to interact with a device. In every non-medical application it is more correct to speak about sEMG, which means "surface EMG", this kind of electromyography denotes

that biometric signals are acquired using electrodes placed on the skin surface, instead of a needle inserted through the skin directly into the muscle fibers. Today there are many fields in which EMG signals are employed, one of the most curious application is the work of Mandryk et al. [40], which uses facial EMG signals as a way to identify human emotional state.
Considering "traditional" movement recognition Wheeler et al. [53] used EMG sensors on the forearm to recognize joystick movement.
Every EMG acquisition procedure consists in two main steps:

1. EMG data have been acquired with an electromyography and features are extracted in order to recognize the movement performed; for this task many methods can be applied: time-domain statistics, short-time Fourier transform, wavelet and many more.

2. data are employed to train a classifier, which is able to match each signal's feature vector with a particular movement. The most employed classifiers are Artificial Neural Networks and Support Vector Machines.

Naik et al. [41, 43] have employed Independent Component Analysis (ICA) in the first phase described above.
It is an iterative technique, where the only model of the signals is the independence and the distribution, this class of algorithms has two main advantages:

- source signals separation without there being any information on the order of the sources;

- crosstalk and noise are substantially subsided.

When the source signals have been obtained, Root Mean Square has been calculated for every set of movement performed. Then the feature vectors obtained are classified with a feed forward back propagation ANN, in order to recognize the movement executed by the end-user. The gesture considered in these experiments are: flexion of the forearm, abduction and flexion of wrist, adduction and flexion of wrist and finger flexion while avoiding wrist flexion; the system described is able to identify all these hand gestures, reaching a 100% accuracy result in some cases.
In [42] Naik et al. compare the performance of four different ICA

algorithms used for the movement recognition system described above. The methods employed in this comparison are:

- **TDSEP - Temporal Decorrelation Source Separation** is based on the simultaneous diagonalization of several time-delayed correlation matrices;
- **FastICA** is a fixed point ICA algorithm that employs higher order statistics for the recovery of independent sources;
- **Infomax - Information Maximization algorithm** is a gradient-based neural network algorithm, with a learning rule for information maximization;
- **JADE - Joint Approximative Diagonalization of Eigenmatrices** is an algorithm based on the joint diagonalization of cumulant matrices under the assumption that the sources have non-Gaussian distribution (this is a requirement for ICA application).

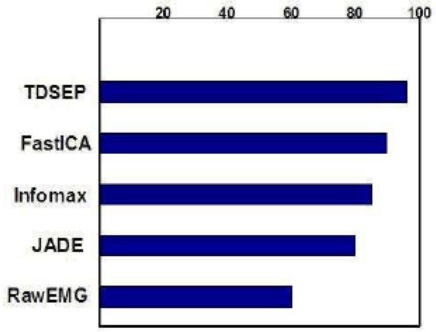


Figure 2.8: ICA algorithms performance comparison

The result of this comparison are shown in figure 2.8, the last bar depicts the system's performance using raw EMG, without any application of ICA algorithm.

One of the most interesting applications of EMG-based HCI is muCIs project by Microsoft Research [47, 48]. In this project sEMG are used to distinguish among three different class of movements:

- hands-free finger gestures;

- hands-busy finger gestures;
- gestures for controlling a portable music player.

A desktop display guides the end-users through training session; it highlights the finger that has to been moved (for the first class of grips), or shows the gesture to be performed, giving the user a visual feedback of his actions. EMG signals are acquired using a BioSemi Active Two system; sensors are placed in a forearm muscle-sensing band (see figure 2.9). The data acquired are splitted and converted in segments

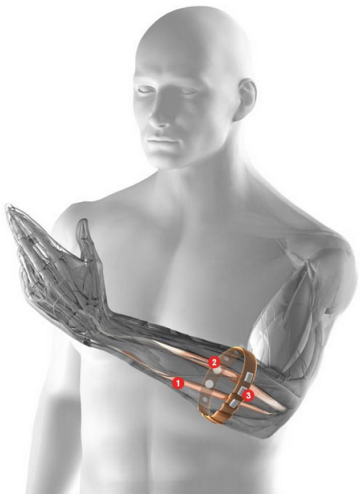


Figure 2.9: Placement of the electrodes in Microsoft muCIs project

suitable for machine learning application. For every segment three set of features are generated:

- **Root Mean Square:** correlates channel's amplitude with magnitude of muscle activity;
- **Frequency Energy:** computed through a FFT for each sample, it is indicative of the temporal patterns of muscle activity;
- **Phase Coherence:** a measurement of the relationship among EMG channels.

The feature vector acquired are employed to train a Support Vector Machine, which obtains a good performance in gesture classification.
The main value of this application is that EMG signals analysis is

employed in an every-day activity like pause a CD-player. Future directions of these projects are the creations of a low-power wireless prototype muscle-sensing unit and the employment of this device for video game interface.
An interesting demonstrative video regarding this muCIs device can be found at the project's main page [15].

2.1.3 Image analysis for gesture recognition

Vision identification devices have been successfully developed for gesture recognition system. These devices use cameras to identify the user gestures - applying image synthesis and analysis algorithms [31] - and provide a visual feedback through a projector or a monitor.
The main advantage of this technology is that it can avoid wearing electrodes or sensor band, moreover, the use of a depth-sensing camera facilitates precise 3D hand positioning and gesture-tracking without requiring the user to wear any type of on-body sensors. However, these devices have several drawbacks; first, they require observable movement or interaction that can be "socially awkward", secondly they are relatively sensitive to environment's light and noise. Moreover, finger contact pressure is not robustly measurable with a camera.
One of the most interesting applications in this field is PlayAnywhere system by Wilson [54], this is a front-projected computer vision-based interactive table system, which uses a compact commercial projection system. The device is composed by a NEC WT600 DLP projector to project a 40" diagonal image onto an ordinary table surface and an infrared light source. A user employs hovers and touches to interact with the device, such features are extracted using a technique which exploits the change in appearance of shadows as an object approaches the surface. The main advantages of this approach are: first of all this input procedure doesn't rely on special instrumentation of the surface, secondly this solution extends the "interaction vocabulary" available for this devices (see figure 2.10).
One of the most innovative device in this field has been recently presented by Microsoft with the code name "project Natal". It is a controller-free device, which combine an RGB camera, depth sensor, multi-array microphone and custom processor running proprietary software.
The whole system is able to track a player's movement in 3D. The RGB

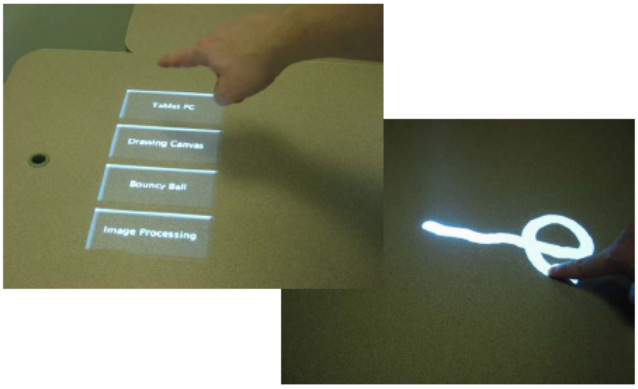


Figure 2.10: The two main ways to interact with Playanywhere. Left: Buttons appear when a finger hovers over the upper left corner of this application. Right: a typical touch interaction.

camera is able to recognize face and facial expression. Depth sensors is an infrared projector combined with a monochrome CMOS sensor, this devices make possible to see the room as a 3D image under any lighting condition. Eventually, the multi-array microphone provides speech interaction with the device. Some information and a related video can be found at the project main site [18].

2.1.4 Hybrid movement recognition system

As a conclusion of this section, another class of devices is shortly presented.
These appliances (named here as "hybrid") combine EMG signal identification with some techniques presented in section 2.1.1 or some devices such as tabletop systems. The main advantage of this configuration is the opportunity to obtain both some data from EMG analysis - muscle contraction and strength - and some information from an inertial device - such as relative position and orientation. The drawback of this solution is the amount of data that have been computed and analyzed to obtain all the information from devices.
One of the most recent projects in this field is the sensor fusion device proposed by Benko et al. [25] which integrates a standard multi-touch tabletop (Microsoft Surface) with EMG signals. In this scenario, touch information sensed by MS Surface are integrated with the data of EMG analysis, which identifies with which finger the end-user has touched

the tabletop. In this way, the "interaction vocabulary" available to interactive surface systems is extended with the opportunity of detecting (theoretically) ten different finger's touches instead of one single touch. Moreover the whole system is provided with the information of fingers' movement when the user is not currently touching the tabletop surface.
Another mixed approach is described in [45]: in this project a videogame control device acquires EMG signals and acceleration data from the forearm. Analyzing the EMG signal, the force exerted by the user can be measured and used as input signal, even when there is no explicit movement of the forearm. Besides, the device can classify hook and straight punch motions of the forearm by analyzing the acceleration data.
This device can be easily adopted in a action virtual-reality game, the user can intuitively make various punching motions, such as punch-like or upper cut-like motion; besides, by measuring EMG signals it is possible to identify some "special attack" completely activated by muscle contraction.
The last cited application is described in [37]: it uses both EMG signals and accelerometer for recognizing some word in German Sign Language, which is a communication way for hearing-impaired people. In this case, the accuracy of the system is essential. For recording a dataset, an Alive Heart Monitor has been employed - which originally is a device for electrocardiogram measures - and a 3-axis accelerometer has been placed on the user's forearm. The Alive system has been attached nearby wrist, for measuring EMG signal generated by Flexor Carpi Radialis.
For recording the most important features from the accelerometer, a 4-order low-pass Butterworh filter and some common statistical features (such as RMS) are calculated on the data obtained. The same Butterworth filter is applied to the EMG signal, followed by the calculation of fundamental frequency and Fourier variance of the spectrum obtained with a Fast Fourier Transform. The obtained feature vectors are classified with Support Vector Machines and k-Nearest Neighbor classifier.
Using the most relevant 15 features, an average accuracy of 99.82% is achieved only for subject-dependent recognition; but this high accuracy doesn't carry over to the subject-independent recognition.
Create a gesture recognition device that is subject-independent is one

of the future direction of this kind of research.

2.2 Mobile devices

In this second section a summary of mobile devices technology is presented.
This part is divided in two main topics: an overview of the main CPU and hardware suitable for mobile application and some hint regarding OS used in smart devices.

2.2.1 CPUs and hardware

CPUs are the main core of all digital platforms. In order to be employed on a mobile device, a CPU must be both efficient and small. This section provides a summary of the most used platforms and CPUs for mobile devices; some of these microcontrollers have been directly employed in Eracle project before adopting Nvidia Tegra.

PIC and dsPIC

PIC (Programmable Interface Controller) is a family of Harvard architecture microcontrollers. They have been originally developed by General Instrument; nowadays one of the most important manufacturer in this field is Microchip Technology [14].
These devices are employed both by professional developers and hobbyists, due to their low costs, serial programming capability, large user base and availability of free development tools like MPLab IDE.
Four configurations of microcontrollers are usually employed: 8-bit, 16-bit, 24-bit and 32-bit. Microchip also developed a particular class of microcontrollers named DSPic, which combines control features of a microcontroller with the computation throughput of a Digital Signal Processing. These characteristics allow developers to employ libraries specific for signal processing, making computation more efficient.
One of the main news in this field is XLP (Extreme Low Power) microcontrollers: this class of products provides the same functionalities of a PIC, including new features for low energy consumption. This peculiarity makes this class of microcontrollers extremely suitable for mobile device application, since battery life has been dramatically extended (see figure 2.11). Low power consumption is obtained mainly due to optimization of instruction set, faster programs execution (that allows the device to enable sleeping mode), sleep current of only 20 nA

and deactivation of unused peripherals.
PIC is employed in many fields, for example:

- automotive;
- intelligent power supply;
- motor control solutions;
- mechatronics;
- battery management solutions;
- utility metering solutions;
- touch screen controllers.

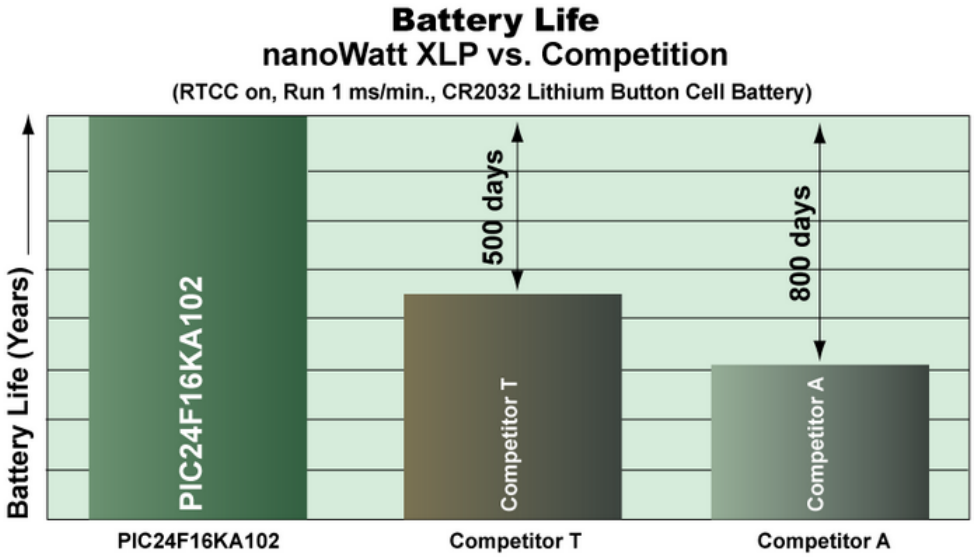


Figure 2.11: Battery life improvement on a PIC24 employing XLP technology

In this field, one of the most interesting hardware solutions is UBW32 [21]. This is a small development board which includes a PIC32 and all the external circuitry to get this microprocessor up and running. The most relevant feature of this solution is that it can be easily connected to a computer and programmed (in a Visual Basic-style language) via USB, without any need of Microchip's programmer.

As shown in figure 2.12, this board provides also a lot of I/O pins, so it can be used as a stand-alone development platform or it can be

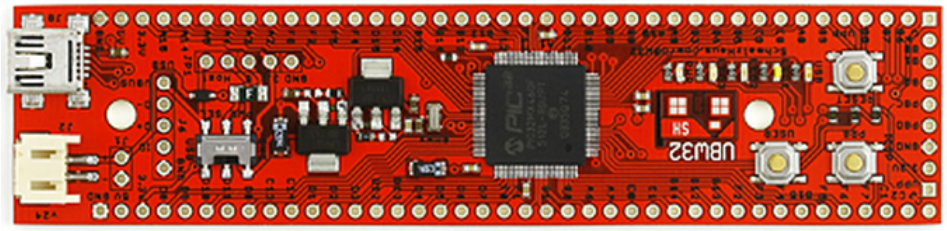


Figure 2.12: UBW board

connected with other appliances to carried out a control device.

ARM

ARM is a family of 32-bit RISC CPU developed by ARM Holdings [4], they have been employed in many embedded systems.

The most well-known application of these kinds of CPUs is Apple

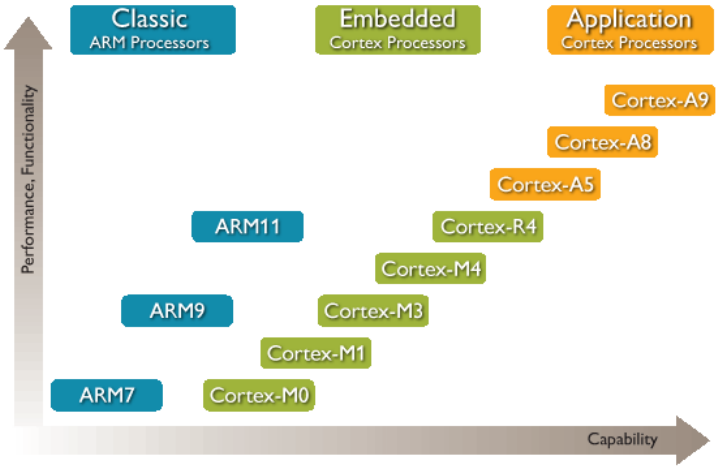


Figure 2.13: A comparison among different classes of ARM CPUs.

iPhone, which employed an ARM11 CPU. As shown in figure 2.13, there are mainly three classes of ARM processors:

- *ARM Classic Processors* are market-proven devices that provide good performance capabilities and efficiency. They are mainly

employed in consumer and home applications.

- *ARM Cortex Embedded Processors* are also divided in two main classes: M-series CPUs have been originally developed for microcontroller domain, therefore they provide highly deterministic interrupt management and low power consumption; they are mainly employed in signal processing devices and smart sensors. R-Series processors have been developed for real-time applications, therefore they ensure strong compatibility with existing platforms; they are mainly employed in automotive braking system and mass storage controller.
- *ARM Cortex Application Processors* are designed for mobile Internet devices, they provide a performance of up to 2GHz in single-core or multi-core architecture. This class of CPUs is also supplied with advanced Floating Point execution units and a new technology for multimedia processing called NEON. ARM Cortex Application Processors are mainly employed in smartphones, eBooks readers and digital TV.

In Eracle project Nvidia Tegra has been employed (see section 5.1) , which combines Dual-core ARM Cortex-A9 MPCore processor and 3D graphics processor. Nvidia Tegra is one of the most employed CPU for mobile devices, it is a full HD ultra low-power mobile Web processor, mainly used for:

- tablets;
- mobile Internet devices;
- smartphones;
- portable media players;
- Internet TV;
- automotive.

Due to the high graphic performance of this CPU, it is also employed in game and graphics design applications.
Today Tegra is distributed for developers as a basic motherboard comprises Tegra 250 SoC and a range of ports for peripherals. Specific SDK for developing with Windows CE or Android are available on Tegra web site [17].

Arduino

Arduino is an open-source electronics prototyping platform based on flexible, easy-to-use hardware and software.
There are many versions of Arduino board, one for each need. The main configurations are [2]:

- **Duemilanove:** it is the basic Arduino USB board (see figure 2.14), that can be easily programmed by connecting it to a computer with an USB cable;
- **Bluetooth:** it contains a Bluetooth module that allows wireless communication and programming;
- **Mini:** it is the most suitable solution for embedded systems, due to its small dimensions;
- **LilyPad:** it is designed for wearable devices, this platform can be sewn onto fabric;
- **Fio:** it is the Arduino board designed to work with wireless signals, it includes a socket for XBee radio, connector for LiPo battery, and integrated battery charging circuitry.

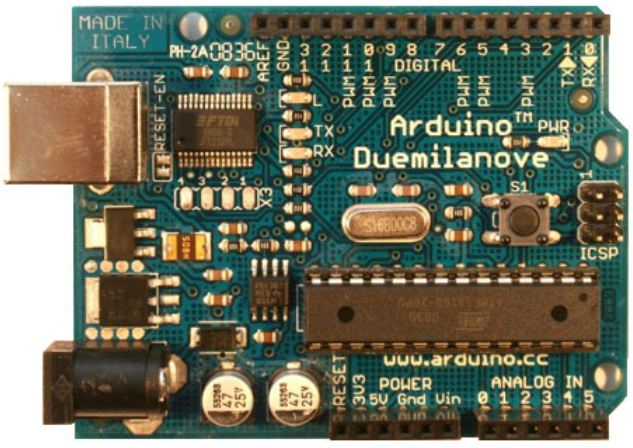


Figure 2.14: Arduino Duemilanove board

Arduino boards mainly uses Atmel ATmega328, an High Performance and Low Power consumption AVR 8-Bit Microcontroller [5].

2.2.2 Operative system

Design an operative systems for a mobile device is a difficult task, mainly because it must handle the "usual" OS activities but in a minimum space and (usually) with reduced software library available.
In this section two main operative systems are presented: Windows CE by Microsoft and Android, the most well-known open source OS for mobile devices.

Windows CE

Windows CE is the smallest Microsoft Windows Operation System: it is a ROM-based OS with a Win32 subset API.
Since version 4.1 it supports .NET Compact Framework, a version of the .NET runtime for mobile and embedded devices. The Compact Framework provides the same powerful .NET runtime environment with a smaller class library.
Windows CE, at its first version (1.0), was just a simple organizer operating system; the second version was released in 1997 with the introduction of the Handheld PC 2.0. The new version included Windows standard network functions, a Network Driver Interface Specification (NDIS) miniport driver model, and a generic NE2000 network card driver, it was also the first edition of the OS to be also available separately from a specific mobile device. In Windows CE 2.01, the C runtime library was moved from a statically linked library attached to each EXE and DLL into the operating system itself. This change lead to a sensible reduction of the size of both the operating system and the applications themselves.
In mid-2000 Windows CE 3.0 was released, the most important feature of this version was its kernel: it was optimized for real-time application and it allowed nested interrupt. There was also many other news in Windows CE 3.0, such as: full COM and DCOM support, file size increased to 32 MB per file, media player control, XML support, remote desktop display support and the introduction of the DirectX API.
The release of Windows CE 4.2 in 2003 was very important for mobile devices, in fact this edition provided: PC-specific APIs that support menu bars, soft input panel and the introduction of hardware paging tables.
The latest release of this OS is Windows CE 6.0, this edition includes

some features highly oriented to mobile technologies, such as smartphones and mobile phones. Just as hints, this release includes: MS Silverlight, Embedded Internet Explorer and touch screen support [26].
Some of the most important changes in Windows CE concern its archi-

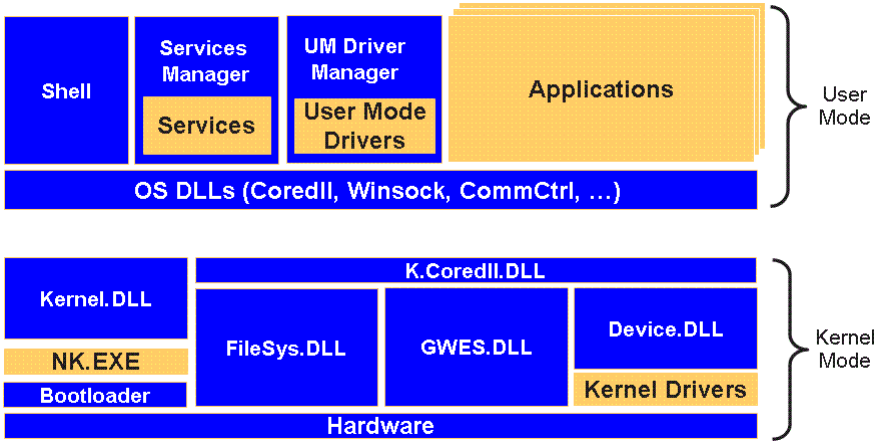


Figure 2.15: Architecture of Windows CE 6.0

tecture and kernel. As shown in figure 2.15, the OS is mainly splitted in two subsystems: user virtual machine and kernel virtual machine. Until Windows CE 6.0, file system, device manager and graphics subsystem were separated (they were named FileSys.EXE, Device.EXE and GWES respectively) and they operated in user mode. This separation made the system robust - since every subsystem was independent and protected from one other - but also decreased performance (due to many process switching).
The new architecture brings all the subsystem into the kernel virtual machine, improving system performance and communication among these three basic processes.
Nk.exe contains the OEM abstraction layer code and a compatibility layer, therefore kernel can be updated without affected OEM code. The DLL named k.Coredll.dll mimics the old Coredll.dll (that was originally placed in user virtual machine) and helps with porting tasks from old applications. A call to an API that requires Coredll is redirect to k.Coredll.dll that simply reflects the request to kernel.dll for processing; as the calls are all within kernel virtual machine, the overall performance is sensibly improved.
The user mode drivers section provides support for third-party drivers

execution, this allocation reduces the process performance but improves security [22].
There are many applications that are suitable for this OS [23]:

- scanners;
- RFID readers;
- eBook readers;
- GPS devices;
- game controllers;
- VoIP phones;
- multimedia portable devices.

One of the most interesting features of Windows CE 6.0 is that it can be flashed on NVIDIA Tegra 250 Developer Kit described in section 2.2.1. This feature make possible to develop applications running on NVIDIA Tegra without handle with hardware or low-level programming.

Android

Android is an open-source operative system for mobile devices, it is based on Linux Kernel version 2.6.
Applications running on Android can be simply developed using Java language.
Android employed Dalvik Virtual Machine, which is an optimized JVM for mobile devices to ensure high compatibility. Moreover, it includes media support for common audio, video, and still image formats (MPEG4, H.264, MP3, AAC, AMR, JPG, PNG, GIF), other than SQLite for structured data storage and modules for wireless communication like Bluetooth and Wi-Fi.
The main architecture of Android is shown in figure 2.16.
The *first layer* includes the main application of a mobile device like a Smartphone: email client, Internet browser, organizer, phone and many more. The *Application Framework* layer provides the underlying services of all applications that are also available to developers. These services are:

- **View system:** which includes a set of Views that can be used in building application, such as lists, grids, text boxes and more;

- **Content Providers** that allows an application to access data on another computer, or shares its own information;
- **Notification Manager** which schedules custom alerts;
- **Activity Manager** that manages the lifecycle of application running on the platform.

The third layer consists of a set of C/C++ *libraries*, which are both used by Android application and exposed to developers. Some of the most important features are System Libraries (System C libraries tuned for embedded Linux-based devices), Media Libraries (designed to handle different media files) and SQLite, which allow the use of databases on smart devices. *Android Runtime* layer include a set of core libraries - that provides a set of functionalities of Java programming language - and Dalvik Virtual Machine, which ensure the compatibility of Java code, adding some features especially designed for mobile devices.

Last layer is *Linux Kernel* which handle services such as security,

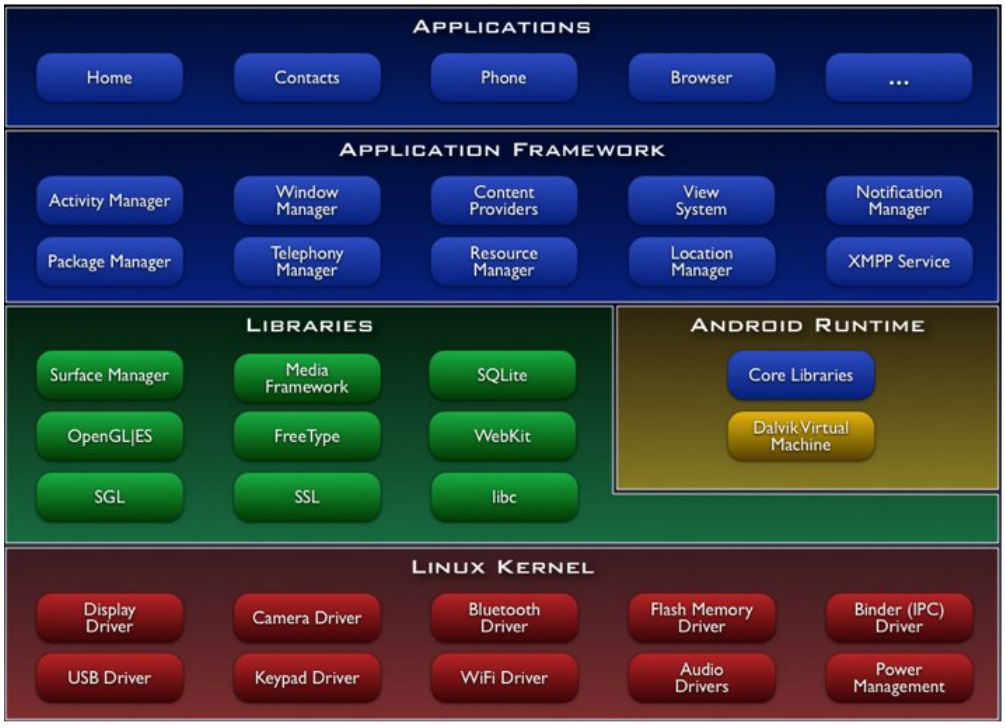


Figure 2.16: Architecture of Android

process management, network stack and driver management.

Due to open-source license and the ease of use of Java code, Android has been used in many portable devices. The first smart device running Android was T-Mobile G1 from HTC, developed in 2008. In the last year some devices such as HTC Desire and Samsung Galaxy S employed Android with high technologies CPUs and hardware [1].

Chapter 3

Project plan and description

"Kirk: All I ask is a tall ship and a star to steer her by.
You could feel the wind at your back in those days. The sounds of the sea beneath you. And even if you take away the wind and the water it's still the same... the ship is in yours. You can feel her. And the stars are still here."

The ultimate computer
Star Trek - The original series

This chapter discusses the aims of Eracle project, the gestures that are employed for Human Computer Interaction and outlines the main differences between this project and previous implementations of EMG-based recognizer devices. It gives reasons for our choices regarding EMG signals as input data and Nvidia Tegra as the computing core of the project.
The last section introduces the general architecture of Eracle, that will be detailed described in chapter 6.

3.1 Project goals

Eracle is a mobile device that recognizes some basic hand gestures processing the EMG signals generated by the forearm muscles.
Recognizers based on EMG signals are usually employed in biomedical field to control prosthesis. Eracle project has a different goal: it is mainly designed to interact with Virtual Reality environments, like video games or augmented reality simulations. With like Eracle, the user can interact directly by its movements, without employing a keyboard or a mouse, making the simulation more immersive. This latter consideration is also supported by the commercial success of devices

like Nintendo Wii or Microsoft Natal. In the first appliance, the controller is mainly employed to track the position of the user's hand, in the second one there isn't any controller at all, since the user gestures are directly identified thanks to image processing algorithms.
It is important that the recognized movement emulates some gestures that are "intuitive" for a user. This consideration is especially true for video games: the user should perform natural and spontaneous gestures to control his avatar. An example of a special charged attack in

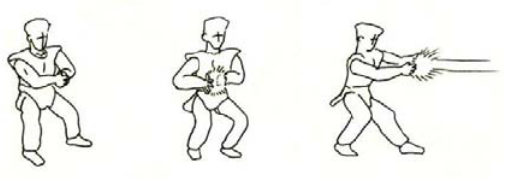


Figure 3.1: Typical motion for a charged attack in Muscleman project

an action games is shown in figure 3.1, this movement is recognized by the *Muscleman* device proposed by Park and Kim in [45]. *Muscleman* has been previously described in section 2.1.4.
Eracle project could be employed in Virtual Reality simulation to track the user's movement. Moreover, it could be connected to a Virtual Reality helmet that provides the visual feedback to the user. The devkit described in section 5.1 provides both USB and Ethernet port, so it could be easily linked to a wide range of appliances.
The sampling devices that provide the input data to the computing core are completely integrated in the acquisition glove (see chapter 6, section 6.2, for more information) that could be worn by individuals with different body size. The computing core of Eracle is fully implemented on Nvidia Tegra 2 CPU. The whole Eracle system (which consists of the sampling unit and the data processing module) weighs only a few grams and the computing core could be fitted in a pocket (see figure 3.2 that depicts the Nvidia Tegra CPU compared to a one dollar coin), so it could be employed by everyone without any muscle fatigue and without any encumbrance. Everyone can use Eracle for Human Computer Interaction, however it is necessary to train the classifier with the specific biometric signal of the real user to achieve the best performance. As outlined in chapter 7, a Neural Network trained to recognize gestures of a specific user is not suitable for identifying

Figure 3.2: Nvidia Tegra compared to a one dollar coin. This SoC easily fit in a pocket

the movements performed by another one. This is mainly due to the differences of arm size, sweating and muscle strength.
However - provided that the system has been set up with the appropriate classifier - it could be employed by different users simply by wearing the acquisition glove on the forearm.

This device could also be employed to control a simple program running on a PC; for example the close hand movement could identify a user assertion (like the *OK* button in a dialog box) and an open hand gesture could represents the user refusal (like the *Cancel* button in a dialog box).
Recent works (such as [29]) describes how devices like Eracle can directly interact with robotic arm; this last application field could be interesting especially in an industrial context. However, it is necessary to improve the global performance in order to apply Eracle to an industrial assembly line.
Another employment field of Eracle is home automation: each gesture would be used to control a domestic appliance like television or air-conditioner. As discussed in section 3.2, EMG-based recognizers are more suitable than image-based devices for this field of application, as they avoid the installation of many cameras in the user's home.

3.1.1 Recognized gestures

Eracle is currently able to recognize up to five movements with accuracy about 90%; however - as described in chapter 8, section 8.1 - we think that the number of recognized gestures could be increased, as well as the global success rate of the device.
The five gestures recognized by Eracle are:

Close Hand

All fingers are clenched into a fist, as shown in figure 3.3. This gesture could represent a user's assertion in typical PC interaction, or an attack movement in a video game application.

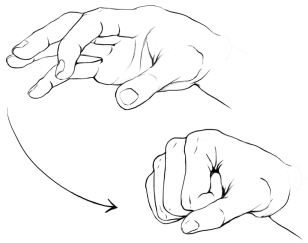


Figure 3.3: Close hand movement

Wrist extension

The fingers are stretched and the hand is flexed towards the back, as shown in figure 3.4. This gesture could be employed to scroll some pictures clockwise.

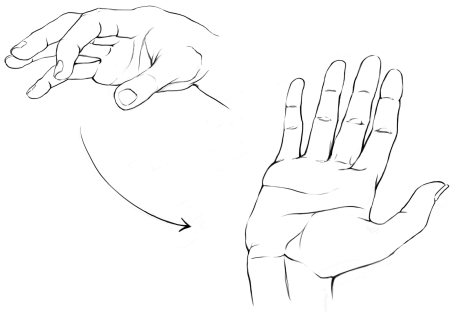


Figure 3.4: Wrist extension movement

Wrist flexion

The fingers are stretched and the hand is flexed towards the palm, as shown in figure 3.5. This gesture could be employed to scroll some pictures counterclockwise.

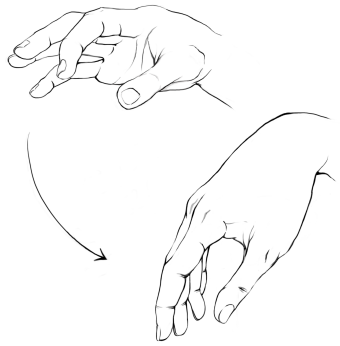


Figure 3.5: Wrist flexion movement

Open Hand

The hand is opened as much as possible, as shown in figure 3.6. This gesture could represent a user's denial, or a defensive position in a video game.

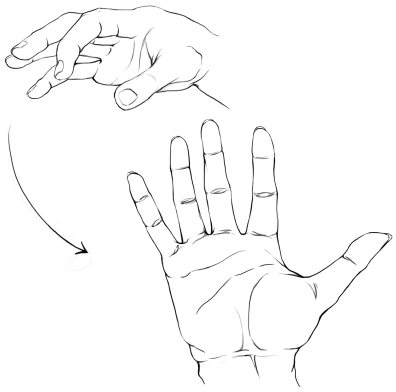


Figure 3.6: Open hand movement

Click

this gesture simulates the left click of a mouse, thus it could be used to select an item on the screen. It is performed by putting the index on the thumb and exerting a slight pressure, as shown in figure 3.7.

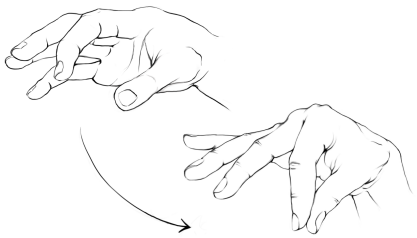


Figure 3.7: "Click" movement

3.1.2 Differences from previous implementations

There are mainly two differences between Eracle and other projects that employ EMG for gesture recognition. The first concerns the *target user.* EMG systems for movement recognition are mainly employed in biomedical field for prosthesis control. It means that the device must be extremely precise, as the amputee employs the prosthesis in daily life and an error in the performed gesture could lead to serious problems. Since these devices must meet the demands of everyday life, hand prosthesis usually provide several different type of grasps, as the user would like to handle different kind of objects. Some examples of typical grasps adopted in hand prosthesis have been described in chapter 2, section 2.1.2. Moreover, the training stage of prosthesis takes a long time as it must perfectly fit the user's needs.
Eracle, instead, is mainly designed for Human Computer Interaction with Virtual Reality environments or video games, thus the user does not want to take a long time to learn how to interact with the application. It entails that the training stage must be as fast as possible, with a minimum number of gesture repetitions. In Eracle project it is sufficient to provide the Neural Network with ten repetitions of each gesture in order to recognize up to five different movements (see chapter 7, section 7.2).
Moreover, Eracle could be employed with good results by everyone (see chapter 8), providing the appropriate training stage. Thus, this device

is suitable for different individuals, with different physique and weight; on the contrary, prosthesis is designed and trained to perfectly fit only one user's needs. This entails that prosthesis is able to recognize more movements and different grasps; instead Eracle can only recognize some basic gestures that make the Human Computer Interaction simpler.

The second main difference between Eracle and the typical application field of EMG concerns the *hardware devices* employed to perform the classifier's training.
The signal processing stage of Eracle is fully developed on the Nvidia Tegra 2 (described in chapter 5 section 5.1) that is a powerful and efficient SoC, but it provides the computing performance of a Smartphones CPU. Instead, almost all the projects focusing on EMG signal analysis employ Desktop PC for data processing. These workstations provide superior speed performance, that entails improved accuracy for gesture recognition tasks.
In developing Eracle, we have mainly focused on system's accuracy in recognizing the performed movement. All the modules of the computing core have been designed to be as independent as possible; this choice is perfect for debug purposes (as we can easily check input and output values of each unit), but leads to an increase in computational speed. However, in chapter 8, section 8.1 we propose some future developments that will shorten the processing time.

3.2 Technological choices: EMG and mobile devices

The two keywords of Eracle project are electromyogram signals and mobile devices, as we have developed a device that recognize hand gestures processing the EMG signals sampled from the muscles, but this appliance must be small enough to be worn by the user.
There are many classes of signals that can be employed to identify the user's movement, and there are also many different devices that can be employed to achieve this purpose. We have decided to employ EMG signals as input data and Nvidia Tegra as computing device, the next paragraph provides some reasons of our choices.

3.2.1 EMG

As discussed in the previous chapter (see section 2.1.2) there are mainly three classes of algorithms that are employed in gesture recognition: EMG, EEG and image analysis techniques. There are some advantages and some drawbacks in all the three cited approaches:

- **EEG:** they provide a huge amount of information about the user movements, as all the signals are sampled directly from the scalp and there is no crosstalking generated by muscles contractions. However this kind of biometric signals are affected by artifacts, moreover, setting up an EEG acquisition procedure is a difficult task, as the electrodes must be placed directly on the user's head, making this acquisition method unsuitable for a mobile application (see figure 3.8).

- **EMG:** these signals are generated by muscles contraction; as a movement is usually performed by several muscles working together this method is affected by signal overlapping called crosstalking. This problem can be avoided employing needle electrodes (that are actually used in medical examinations), but they are totally unsuitable for a Virtual Reality or a Human Computer Interaction application.
  With this technique is possible to recognize about four or five basic movements.

- **Image analysis techniques:** this kind of devices have been recently employed for a game controller based on gesture recog-

Figure 3.8: Electrodes placement in EEG examination. It is obvious that this kind of sampling procedure is unsuitable for HCI

nition developed by Microsoft (project Natal, for more information see 2.1.3). Image analysis offers a wide range of information about the user's movements; with this technology it is possible to recognize at least ten different gestures. The main drawback in using this kind of devices is the number of cameras that must be employed in order to obtain a good result.

Taking into account these simple considerations, we have decided to employ EMG as the input signals of Eracle. Moreover, these kind of biometric signals have already been used with good result by Naik et al. in [41] and Benko, Saponas et al. in [25]. This last project has been described in section 2.1.2 of the previous chapter.

3.2.2 Nvidia Tegra: a mobile processor

Eracle project is also focused on mobile devices, thus, there is no need to connect the device to a PC in order to use it. The whole acquisition procedure is carried out by the acquisition glove (see section 6.2), which include the sEMG electrodes and the EMG board (see section 5.2), as the signal processing and gesture recognition tasks are carried out by Tegra CPU (see section 5.1). The main advantage of this SoC (System on Chip) processor is that it offers a good computing performance in

compact size; for both these two reasons it is mainly employed in Smartphones and Netbooks. The main core of Nvidia Tegra is a Dual-core ARM Cortex-A9 CPU. We have selected Nvidia Tegra among many other CPU architectures mainly due to its high performance and low power consumption.
There are many other processors designed for mobile computing, such as Apple iPhone 3G, Intel Atom and Samsung S5PC110. Figures 3.9 and 3.10 depict the results obtained by ARM and Atom CPU running CoreMark benchmark. This suite has been developed by the Embedded Microprocessor Benchmark Consortium ([9]) and it is specifically designed for approximating the real-world performance of an embedded system. The number returned by this application is a global score that summarize the processor's performance.

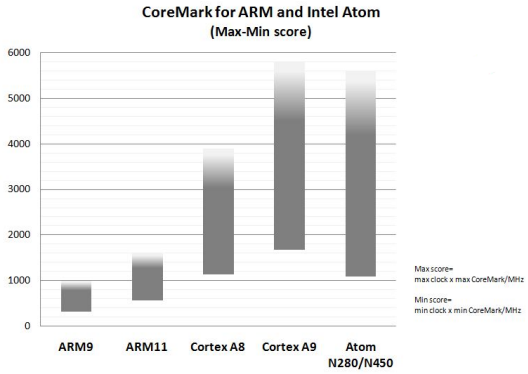


Figure 3.9: Maximum and minimum performance of some embedded [8]

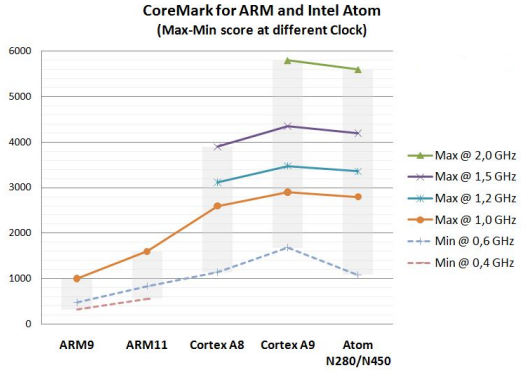


Figure 3.10: Performance of embedded CPU at different clock rate [8]

Nvidia Tegra 2 is mainly employed in Smartphones and Tablet PC, figure 3.11 shown a performance comparison between different Smartphones using the Quadrant benchmark package. Netbook Toshiba AC100 (the one named *"your device"* in figure 3.11) achieves the best result in the performance comparison. This device is equipped with Nvidia Tegra 2 and runs Android 2.1 as OS. The reduced size and the

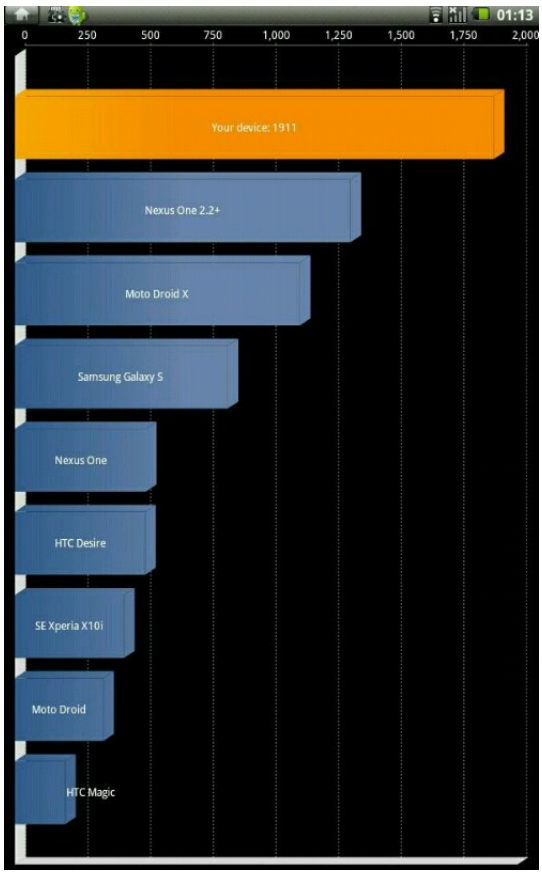


Figure 3.11: Performance comparison of different Smartphones using the Quadrant benchmark package. The one named "your device" is a Toshiba AC100 Netbook, that is equipped with Nvidia Tegra 2 and Android 2.1

low power consumption of Nvidia Tegra make possible the fulfillment of a completely wearable system. This means that the whole computing core of Eracle project can fit in a pocket, and it could be easily connected to an external appliance through wireless technology like ZigBee, WirelessHART or MiWi (see section 8.1 in chapter 8). Thus, the user can perform his movements in a very natural way, without any

hindrance caused by the sampling or computing devices.
The main features of a wearable device are:

- it is designed for a continuous use and it operates always in an active mode;
- it should improve the sensory capabilities of the user and it must not hinder the user's movements;
- it should adapt itself to the environment;
- as a wearable computer should be employed in daily life, it should be easily connected to a wide range of appliances, using many different communication protocols.

We have developed Eracle following these four guidelines, but realizing a wearable computer is a very difficult task, therefore there are many features that can be improved. Section 8.1 in chapter 8 reports some possible future developments following the concepts of wearable computer.

3.3 General architecture of Eracle project

The aim of Eracle project is to achieve a fully wearable system for gesture recognition based on EMG analysis.
Figure 3.12 depicts the general architecture of the project. At the beginning of the acquisition chain there is the user's forearm, it means that the first step consists in acquire the EMG signals generated by the user's movements. We have focused only on hand gestures, which can be identified by the forearm muscles contraction; more details on EMG signals can be found in appendix B.

The next step in the acquisition chain is the *acquisition glove*, that can be easily worn by the user on the forearm. As depicted in figure 3.12, this device hosts two different modules:

- the sEMG electrodes employed for signal sampling;
- the EMG board that carries out some basic filtering on the raw signal and converts it to digital values.

The last section is the biggest one: it provides the filtering of the EMG signals and the recognition engine. It is fully implemented on Tegra Devkit described in section 5.1 in chapter 5.
This last module is based on two executable files: EracleACQ and EracleREC.
Both the applications provide the following units:

- a *Serial Port Manager* that handles the communication between Devkit and EMG Board;
- the *Parser* module, that split the input data into three different listings (one per channel) and removes some spurious data;
- the *FastICA* module that process and filter the raw input data;
- a *RMS* unit that computes the Root Mean Square value for each channel.

The main difference between the two applications is in the last module. In EracleACQ it is called *NN Train*, it trains the Neural Network that will recognize the user's movement; in EracleREC the last unit is named *NN Classify,* as it handles the gesture recognition stage, employing the previously trained Neural Network.

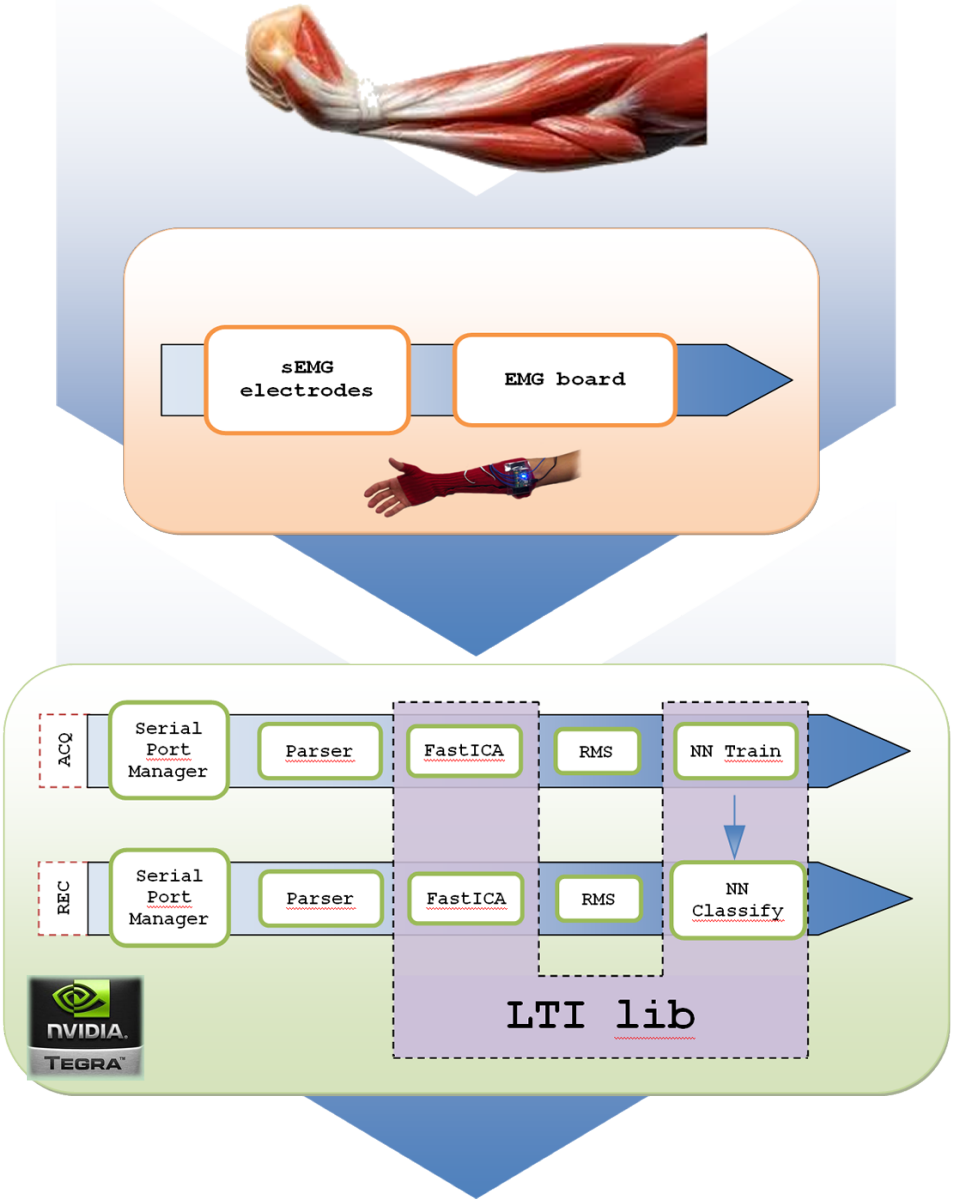


Figure 3.12: General architecture of Eracle project. The system is mainly divided in two different units: the acquisition glove - that carries out EMG sampling and analog to digital conversion - and the computing core - which provides the data processing. This last one is fully implemented on Nvidia Tegra 2

Another difference between the two executables is that in EracleACQ the described modules are implemented on their own, while in EracleREC the last four units are implemented in the same function. The main reason of such choice is the computational performance: every module of EracleACQ is fully independent by the others; it means that it takes some files as input and generates some files as output, and there is no cooperation between them. This choice entails that every unit could run on his own. The main drawback is that the computational speed is reduced, mainly due to the big amount of I/O operations performed. However, this is not a lack, as the data sampling for Neural Network training is usually executed as batch process.
Instead, EracleREC directly interacts with the user, so its computational performance can't be too low; moreover it handles just one single movement (instead of EracleACQ, that processes about ten acquisitions for each movement). For this reason the modules that perform signal filtering and gesture recognition (*Parser, FastICA, RMS and NN Classify*) are implemented together, avoiding the huge amount of I/O operations performed by EracleACQ. This feature improves the computational speed, but the system can't be consider as a real time application.
Chapter 8, section 8.1 presents some possible future developments to improve the recognizer performance.
As shown in figure 3.12 the three modules *FastICA, NN Train* and *NN Classify* are developed employing the features provided by LTIlib, a mathematical library mainly used in image processing and computer vision. The modules of Eracle project will be detailed described in chapter 6.

Chapter 4

Independent Component Analysis

"McCoy: In this galaxy, there's a mathematical probability of three million Earth-type planets. And in the entire universe, three million million galaxies like this.
An in all of that, and perhaps more, only one of each of us. Don't destroy the one named Kirk."

Balance of terror
Star Trek - The original series

This chapter provides both a basic introduction to Independent Component Analysis (ICA) and some technical details about the application of this method to biometric signals elaboration.
In the first section some mathematical and statistical properties of the algorithm are discussed, focusing both on theoretical and implementations aspects. Finally, the last section provides some hints on how this algorithm can be applied to EMG and EEG signals and introduces some problems related with this choice.

4.1 Principles of ICA

Independent Component Analysis is a linear transformation method: thus, it is an algorithm that represents multivariate data as a linear transformation of the original statistical observations. ICA algorithms search for the transformation that minimizes the statistical independence of the original representation's components, highlighting the essential structure of the observed data.

Considering a vector $\mathbf{x}$ of m observations, an unmixing matrix $\mathbf{W}$ and a vector $\mathbf{s}$ of m sources ICA can be applied to $\mathbf{x}$ to obtain a linear transform $s = Wx$ maximizing a function $F(s_1...s_n)$ that measures the independence between the s_i components.
This definition could also be stated in a more practical way as:

Definition 4.1 (ICA)**.** ICA of a random vector of statistical observation $\mathbf{x}$ of m components consists of estimating the following generative model for the data:

$$x = As \tag{4.1}$$

Where $\mathbf{s}$ is the vector of n sources that are assumed to be independent and A is the constant mxn mixing matrix, which describes the linear mix of the original signals.

Applying ICA requires that at least three main constraints have been respected:

1. all the independent components s_i (except for maximum one component) must be non-Gaussian;
2. the number of m observation of vector $\mathbf{x}$ must be at least as large as the number of the independent sources n of vector $\mathbf{s}$ ($m \geq n$);
3. the mixing matrix A must be of full column rank.

The first restriction is necessary as for Gaussian random variable uncorrelatedness implies independence. In fact statistical variables are independent if the density function can be factorized:

$$f(y_1, ..., y_n) = f_1(y_1)f_2(y_2)...f_n(y_n) \tag{4.2}$$

Instead, statistical variables are uncorrelated if:

$$E\{y_i y_j\} = E\{y_i\} E\{y_j\} \tag{4.3}$$

Statistical independence is a much stronger requirement than uncorrelatedness, but if the $y_1...y_n$ statistical variables have a joint Gaussian distribution, this two properties are equivalent. Thus any decorrelating representation would give independent components searched by ICA.
Anyway, it is important to remark that even though some components of source vector $\mathbf{s}$ are Gaussian it is still possible to identify the non-Gaussian independent components.

4.2 Fields of application of ICA

The main application framework of ICA is the Blind Source Separation (BSS) problem [36], that can be intuitively described by the *cocktail party problem*. In this scenario there are several people speaking simultaneously in the same room: the problem is to separate the different voices using the recordings of several microphones in the area.
Referring to the ICA model:

- the *microphones* are the *statistical observations* of vector **x**;
- the *voices* are the *sources* of the vector **s**.

A schematic representation of cocktail party problem is shown in figure 4.1. Another practical and popular use of ICA is denoising, that

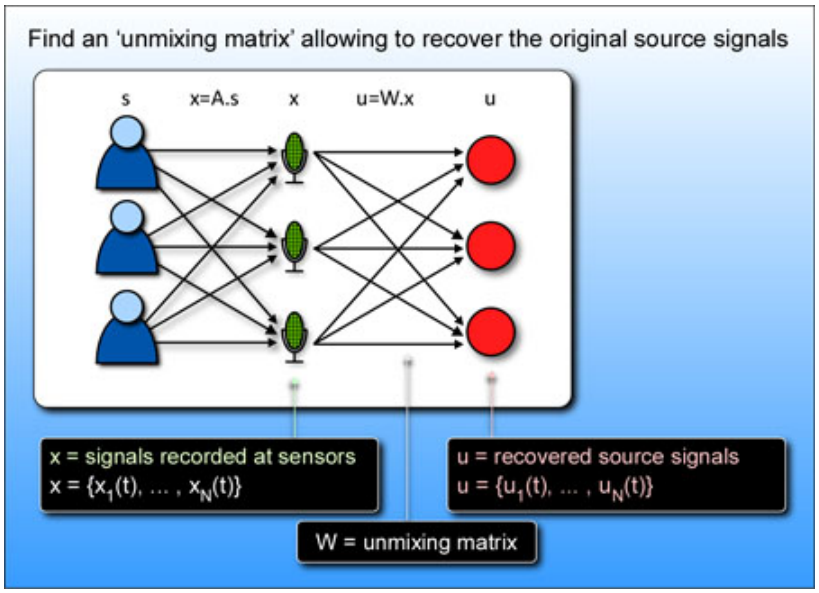


Figure 4.1: Representation of cocktail party problem

consists in separating the original source of signal from overlapped noises.

One of the most promising fields of application of ICA is Feature Extraction, this technique is mainly employed in neuroscience for the extraction of low-level features of natural image data [44]. An interesting comparison between the features extracted by ICA and the simple cells

in primary visual cortex is reported in [50]. The authors also point out that the best results are obtained using video sequences instead of still images.
The quality of the results is similar to those obtained by Mallat with wavelet in [39].

4.3 Estimating data model using ICA

The estimation of a data model using ICA is performed in two different steps: first, it is necessary to choose an objective (or contrast) function to be minimized, then an algorithm for performing such minimization must be selected.
The properties of ICA method are sensibly affected by these two choices, in particular:

- the choice of the contrast function affected the statistical properties of the ICA method, such as robustness and variance;
- the choice of the algorithm affected properties such as convergence speed, memory requirements and numerical stability.

4.3.1 Contrast functions

In addition to the statistical properties of ICA, the choice of contrast function also affected the way of estimating the independent components (ICs). There are two approaches: computing all the ICs at the same time, or calculating only a single feature. In the second case the procedure can be iterated to obtain several independent components.

Multi-unit contrast functions

For the first class of approach **multi-unit functions** are employed, one of the most widely used is the log-likelihood function:

$$L = \sum_{t=1}^{T} \sum_{i=1}^{m} \log f_i(w_i^T x(t)) + T \ln |\det W| \tag{4.4}$$

where W is the umixing matrix and x is the vector of statistical observations.
The main advantage of this approach is that (imposing some regularity conditions) it is asymptotically efficient. The main drawback is that it is necessary to know the probability densities of the independent components and estimating them is a difficult task.

Another widely used contrast function is the mutual information I of the random vector of observation $y_1, ..., y_n$, that can be defined as:

$$I(y_1, y_2, ..., y_m) = \sum_i H(y_i) - H(y) \tag{4.5}$$

where H denotes the differential entropy of a vector of random statistical variables:

$$H(y) = -\int f(y) \log f(y) dy \tag{4.6}$$

The mutual information is a measure of the dependence between variables: it is zero if and only if the variables are statistically independent, so a way to estimate the ICA model consists in finding a transform that minimizes this value.
The main drawback of mutual information is that it is difficult to estimate, because to compute entropy it is necessary to assess the density of the observations vector.
This problem can be solved using high-order cumulants, which are constants that can be computed expanding as a Taylor series the logarithm of the characteristic function of a scalar random variable of zero mean. The first three cumulants have a really simple expression: $k_1 = E\{x\} = 0$, $k_2 = E\{x^2\}$ and $k_3 = E\{x^3\}$. The most practical and interesting cumulant is the fourth, called kurtosis:

$$k_4 = E\left\{x^4\right\} - 3(E\left\{x^2\right\})^2 \tag{4.7}$$

This cumulant can be consider as a measure of the non-Gaussianity of x, thus for a Gaussian random variable kurtosis is equal to zero.
Kurtosis is widely used in ICA methods, as it has these two properties:

$$kurt(x_1 + x_2) = kurt(x_1) + kurt(x_2) \tag{4.8}$$

$$kurt(\alpha x_1) = \alpha^4 kurt(x_1) \tag{4.9}$$

Using cumulants the mutual information can be (approximately) computed as:

$$I(y) \approx C + \frac{1}{48} \sum_{i=1}^{m} [4k_3(y_i)^2 + k_4(y_i)^2 + 7k_4(y_i)^4 - 6k_3(y_i)^2 k_4(y_i)] \tag{4.10}$$

where C is a constant and the observation y_i must be uncorrelated. However, this approximation holds only if the probability density of observations is not far from Gaussian.

One-unit contrast functions

Instead of estimating the whole ICA model it is possible to use **one-unit contrast functions**, which compute only a single independent component; iterating the procedure it is possible to estimate all the ICs derived from the statistical observations.
Once the first independent component has been computed, it is possible to obtain the others maximizing the contrast function under the constraints of decorrelation with respect to the ICs already found; this incremental approach is called deflationary.
The main advantage of one-unit contrast functions is that the computational complexity of ICA is noticeably reduced, especially if the input data has a high dimension.
With these contrast functions the differential entropy defined in equation 4.6 can't be applied, because that expression is not invariant from scale transformations. Therefore a linearly invariant version of such feature is computed: it is called negentropy, which means negative normalized entropy. This value is always non-negative and it is zero if and only if the statistical observations have a Gaussian distribution:

$$J(y) = H(y_{gauss}) - H(y) \tag{4.11}$$

where y_{gauss} is a Gaussian random vector of the same covariance matrix as y (which is the vector of statistical observations). Once negentropy is defined, it is possible to determine the mutual information as defined in equation 4.5:

$$I(y_1, y_2, ..., y_n) = J(y) - \sum_i J(y_i) \tag{4.12}$$

As discussed with respect to multi-unit contrast functions, it is possible to compute the ICs finding a representation in which mutual information is minimized. Unfortunately - as in multi-unit case - mutual information is difficult to estimate, so this feature can be approximated by high-order cumulants (whit some additional difficulties with respect to multi-unit contrast functions [32]).
Kurtosis approximation can be applied also with one-unit contrast functions; in this case it is defined as:

$$kurt(w^T x) = kurt(w^T As) = kurt(z^T s) = \sum_{i=1}^{m} kurt(s_i) \tag{4.13}$$

where $z = A^T w$.
Under the constraint $\|z\|^2 = 1$, it is possible to obtain the ICs maximizing the expression 4.13. However this solution is far from optimal mainly for two reasons: first, because higher-order cumulants are sensitive to outliers and secondly because this features are largely independent by the structure in the middle of the distribution and are mostly correlated to the tails of the statistical density.
For ICA another one-unit contrast function has been introduced in [32] as a generalization of kurtosis that tries to combine some features such as:

- no prior knowledge of the densities of the ICs;
- simplicity of algorithmic implementation;
- interesting statistical properties.

This objective function is called generalized contrast function and it practically a measure of non-normality; it can be constructed using any functions G and considering the difference of the expectation of G for the actual data and the expectation of G for Gaussian data.

4.3.2 Algorithms for ICA

Once a contrast function has been defined, it is necessary to select a way to optimize it, choosing an appropriate algorithm.
Some preprocessing is usually applied before computing the ICs with the selected algorithm, mainly it consists in sphering the input data. It means that the observed variable $\mathbf{x}$ of the classical ICA model $x = As$ is transformed to a variable $\mathbf{v}$

$$v = Qx \tag{4.14}$$

such that the covariance matrix of $\mathbf{v}$ is equal to unity ($E\left\{vv^T\right\} = I$). This transformation is always possible and - even in cases in which it is not strictly necessary - improves the convergence speed of the selected algorithm.
The variable $\mathbf{v}$ can be defined as (from 4.1 and 4.14):

$$v = Bs \tag{4.15}$$

where $B = QA$ is an orthogonal matrix, because:

$$E\left\{vv^T\right\} = BE\left\{ss^T\right\}B^T = BB^T = I \tag{4.16}$$

remembering that a square real matrix B is orthogonal if $B^T B = BB^T = I$.
The main advantage of preprocessing is that the problem of finding an arbitrary matrix A defined in 4.1 has been reduced to the simpler problem of finding an orthogonal matrix B, which can be used to obtain the ICs simply by transposing it:

$$\hat{s} = B^T v \tag{4.17}$$

instead of computational-expensive inversion of matrix A.

The first ICA algorithm was introduced by Jutten and Herault in [36] and it is inspired by neural networks. The matrix of weights is updated according to the rule:

$$\Delta W_{ij} \propto g_1(y_i) g_2(y_j) \tag{4.18}$$

for elements outside the diagonal (thus when $i \neq j$) and it is zero for the diagonal terms. The two relations g_1 and g_2 are odd non-linear functions. The output terms y_i are computed at every iteration as:

$$(I + W)^{-1} x \tag{4.19}$$

The two main drawbacks of this algorithm are that it converges only under severe restrictions, and it is computationally expensive (mainly due to the matrix inversion computed at every iteration).
These two disadvantages can be (partially) resolved using non-linear decorrelation algorithms such as EASI, introduced in [27] which proposes the following learning rule, that avoids the matrix inversion operation:

$$\Delta W \propto (I - yy^T - g(y)y^T + yg(y^T))W \tag{4.20}$$

Another interesting class of algorithms is based on maximization of network entropy (infomax), it is similar to maximum likelihood approach. They are mainly based on (stochastic) gradient ascent for objective function. The main drawback of this class of algorithms is that they converge very slowly, but speed can be improved by preprocessing data with whitening.

One of the most practical and widely used algorithms for Independent Component Analysis is FastICA. It is a fixed-point algorithm originally

proposed in 1997 by Hyvärinen and Oja [32].
It requires sphering preprocessing and the learning rule can be implemented as:

$$w(k) = E\left\{xg(w(k-1)^T x)\right\} - E\left\{g'(w(k-1)^T x\right\} w(k-1) \quad (4.21)$$

The non linear function g is the derivative of the function G defined in general contrast function introduced in [32].
Several systems can estimate the ICs using deflationary (see 4.3.1) or symmetric method: in this last configuration the ICs are all estimated in parallel.
The convergence speed of the algorithm is high, as FastICA uses sample averages computed over larger amount of data, instead of using every data point immediately for learning. An interesting property is that symmetric FastICA is essentially equivalent to a Newton method for maximum likelihood estimation, that makes this method suitable both for one-unit and multi-unit contrast functions.

4.4 ICA for biometric analysis

In biometrics analysis ICA methods are mainly employed for denoising. The main problem in using ICA methods with noisy signals is the lack of robustness of the algorithms, however - for EMG data analysis - these approaches have been used with good results by Naik et al. ([43], [42] and [41]). The main difficulty of EMG signals is that they have a probability density close to Gaussian, while noises (such as motion artifacts) have non-Gaussian distribution (as discussed in section 4.1, ICA methods cannot deal with purely Gaussian distribution, because in this case uncorrelatedness entails statistical independence). It is important to underline that EMG signals have probability density that is only **close to Gaussian**, so ICA methods can be successfully employed in some denoising application using a Gaussianity-based contrast function, such as:

$$G(x) = -\frac{1}{\alpha}\exp\left(-\frac{\alpha}{2}x^2\right) \tag{4.22}$$

Moreover, EMG analysis for gesture recognition can be considered as practical implementation of BSS problem (see section 4.2) where:

- the sources are the signals produced by the muscles (with reference to the cocktail party problem they are the people's voices);
- the statistical observations are the data acquired with the electrodes (with reference to the cocktail party problem they are the microphones).

From this point of view, ICA is also used to reduce the cross-talking between two or more muscles that are activated in the same contraction, thus the obtained ICs are the real signals generated by each motor unit. These two considerations are also supported by [43].
Figures 4.2 and 4.3 depict an example of ICA application in biometric signal analysis.

Figure 4.2 shows the input source data corresponding to a wrist extension; note that the y-axis values are the same for all the three graphs. Figure 4.3 shows the same signals processed by FastICA algorithm. First of all the amplitude values of the three signals have been normalized. Moreover the signal sampled on channel 2 - that is very noisy, maybe due to crosstalking - has been limited by ICA algorithm. On the contrary, source signal sampled by channel 1 has been boosted,

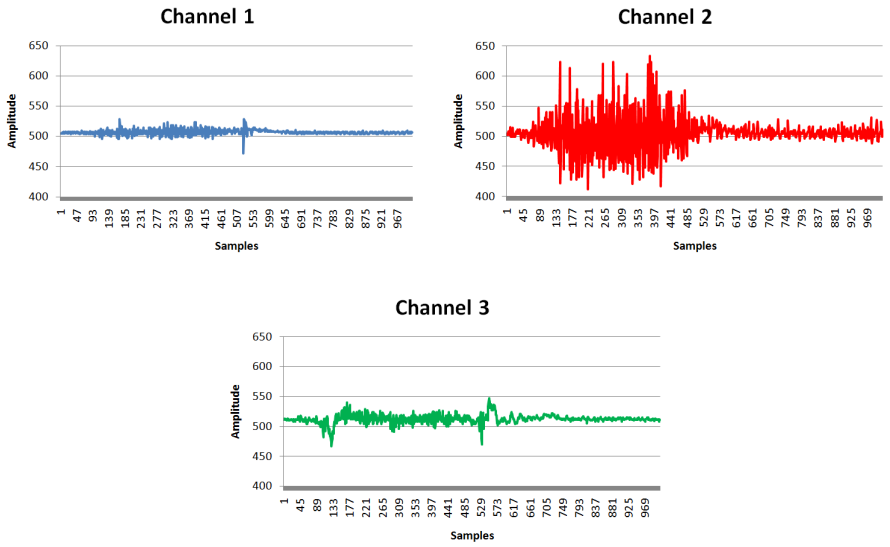


Figure 4.2: The raw signals generated by a user performing a wrist extension. Note that channel 2 is really noisy, while channel 1 is extremely weak.

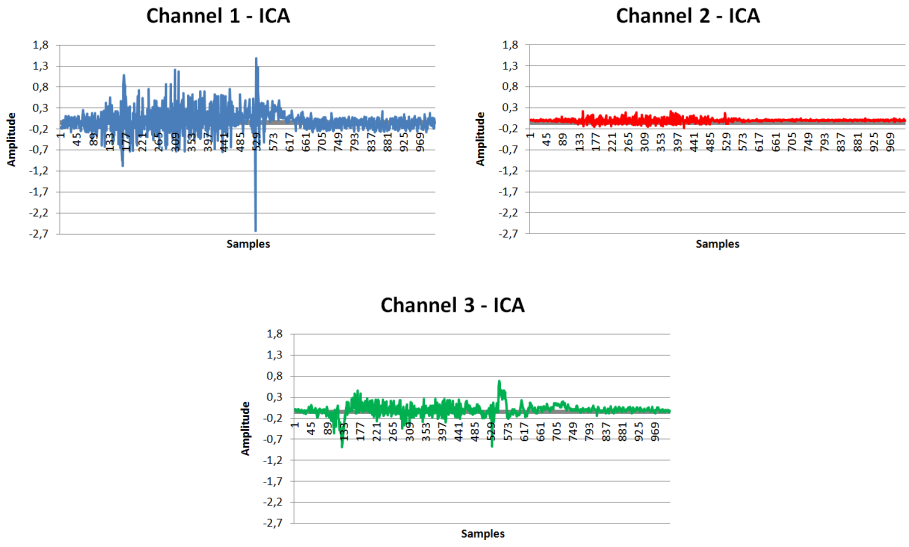
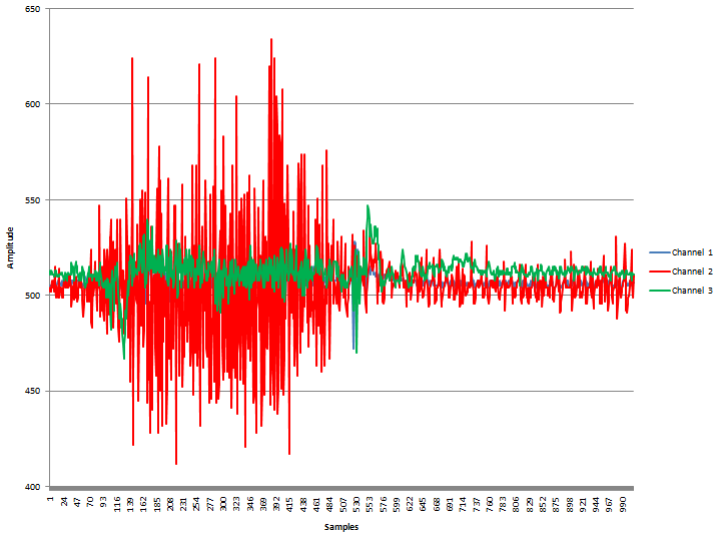
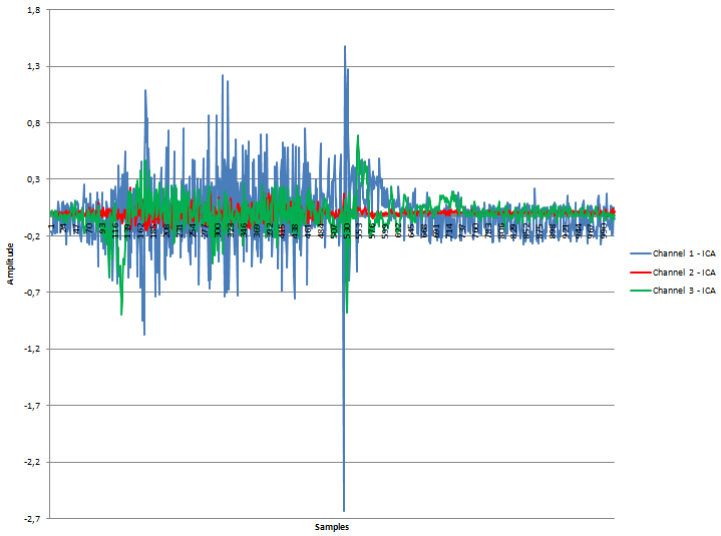


Figure 4.3: The input signals after FastICA filtering. Note that signal 2 (the noisiest one) has been subsided, while signal 1 has been amplified.

while the input signal on channel 3 remained virtually unchanged. Figure 4.4 depicts all the three signals before and after the application of the ICA algorithm. Removing the noise from the signals it is possible to correctly extract some features (like the RMS) that identify the gesture performed by the user.



(a)



(b)

Figure 4.4: The three input files before (a) and after (b) the FastICA filtering. Note the amplitude difference of signal 2 and 1.

There are also other drawbacks in employing ICA for EMG analysis: first of all, the exact amplitude and sign of independent components can't be determined and, secondly, the order of the ICs cannot be determined. Moreover, ICA employing high-order statistics (like kurtosis) aren't performing well on EMG analysis. Maybe this lack of performance is due to the need of a larger dataset, that isn't usually available in HCI application base on EMG analysis. This consideration is also supported by [42], in which a second order statistic-based algorithm (TDSEP) gives an overall efficiency of 97% in hand gesture recognition.

ICA methods have also been applied in electroencephalography for separating the EEG from artifacts (for more information about EEG see 2.1.2). As described in [51] the application of such method leads to some interesting and promising results in EEG analysis, however the task of canceling artifacts from EEG signals remains a central problem in electroencephalography data analysis.

Chapter 5

Hardware devices

"Spock: I saw VGer's planet. A planet populated by living machines. Unbeliavable technology. V'Ger has knowledge that spans this universe. And yet, with all its pure logic... V'Ger is barren. Cold. No mystery. No beauty. I should have... known...
Kirk: known? known what? what should you have known?
Spock: (Holding Kirk's hand) this simple feeling ... is beyond VGer's comprehension. No meaning. No hope. No answers. It's asking questions: Is this... all that I am? Is there nothing more?"

Star Trek - The motion picture

This chapter provides a description of the devices employed in Eracle project.
The first section is focused on Nvidia Tegra 2, the CPU that carries out all the signal processing and recognition procedures. The EMG board employed for electromyogram signals acquisition and digital conversion is presented in section two. The last paragraph presents a brief description of the FTDI serial driver, which has been employed to connect sEMG board to Tegra.

5.1 Nvidia Tegra 2

Nvidia Tegra 2 is the core of Eracle wearable system; it is a system-on-Chip (SoC) mobile processor, specifically designed for high performance computing on smart devices like tablets, smartphones and mini-laptop.

5.1.1 Tegra CPU architecture

The Nvidia Tegra 2 mobile processor is the functional combination of eight different modules (see figure 5.1):

- **Dual-Core ARM Cortex A9 CPU**:
  this kind of processors is an ideal choice for mobile platforms, as they combine high-efficiency power consumption and increased peak performance for most computational-demanding applications. The Tegra 2 ARM CPU provides a performance of 1GHz per core; when the processor is not in use it is turned off, to improve battery life. The last version of this CPU provides a really scalable four-core architecture, with a performance of 2GHz per core, an 8-stage pipeline, up to 64 KB of four way associative L1 caches and up to 8MB of L2 cache [3].

- **ARM 7 processor**:
  this CPU is employed for tasks that have lower performance requirements, or for multimedia files processing.

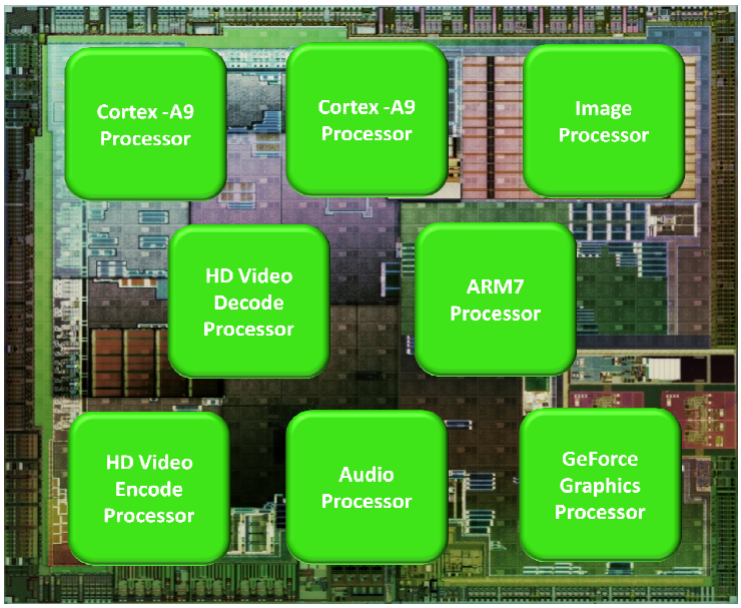


Figure 5.1: The eight modules of Nvidia Tegra 2

- **Ultra Low-Power Graphics Processor (GPU):**
  it is a processor with dedicated hardware optimized for graphics

operations such as Flash animation rendering or decoding. It is also capable to handle the workload requested by modern game engines with minimal battery consumption.

- **HD Video Decode Processor:**
  this processor decodes video streams that are played from a file or from the network; it manages all the three types of Flash video formats: H.264, Sorenson and VP6-E. Using this decoder instead of a general-purpose CPU provides high quality images and improves the battery life.

- **HD Video Encode Processor:**
  this device handles encoding procedure for streams coming in from an HD video image sensor at 30 fps.

- **Audio Processor:**
  it provides a high quality output radio with very low power consumption, for example it consumes less than 30 mW of power while playing back a 128 Kbps MP3 file.

- **Image Signal Processor (ISP):**
  this device provides some graphic elaboration (such as white balance, edge enhancement, and noise reduction) for pictures up to 12 megapixel resolution.

The best power management is ensured by NVIDIA Tegra Global Power Management System, that uses hardware monitors information (e.g. temperature and incoming request patterns) and a feed-forward control algorithm to determine the optimal operating frequency and voltage for the active processors.
Some examples of battery life achieved thanks to NVIDIA Tegra Global Power Management System are shown in the following table: Tegra is

Use Case	**Battery life**
Standby	2000 hours
128 kbps MP3 music playback	140 hours
HD video playback on external display (via HDMI port)	16 hours
HD video playback on local lcd	8 hours

Table 5.1: Tegra use-cases and related power consumptions [17]

released also as a developer kit; in Eracle project the NVIDIA Tegra

250 developer kit has been employed.
In addition to the previously described features of Tegra CPU, this development board provides some extra interfaces and modules such as 1 GB of RAM, Wi-Fi, Bluetooth and USB input. As shown in figure 5.2,

Figure 5.2: NVIDIA Tegra 250 developer kit. The SoC is only the square in the centre, while the other ports are expressly designed for the development board.

the devkit includes:

- *15V power jack* for power supply;
- *VGA jack* for video output;
- *HDMI jack* for digital output display;
- *Wi-Fi antenna jack;*
- *3 USB-A input port* that provide connections with basic peripherals like keyboard or mouse;
- *"ACOK" configuration switch* which is used to switch the power behavior of the devkit between BATT or NORM configuration;
- *power button* to turn the device on and off;

- *recovery button* that places the devkit in recovery mode; it is a special configuration in which the device is ready to receive a new OS image;
- *reset button* for soft reset of the board;
- *microphone and headphone jack* for sound output;
- *Ethernet jack;*
- *SD slot card;*
- *USB-mini jack* to connect the devkit to the host pc.

5.1.2 Developing software on Tegra

The previously described devkit is a completely novelty in the field of embedded CPU, mainly because it combines the reduced size (that makes it suitable for wearable applications) and the high computing performance.
This processor is not available for purchase on Italian market, it has been provided to some technological partners of Nvidia Corporation. One of these partner is Seco s.r.l.([19]), that provides the devkit employed to develop Eracle project.
The reduced spread of this kind of platform makes it suitable for the development of a completely new project. However, building a completely new application starting from scratch is a difficult task, mainly due to the lack of supports and information regarding this processor.
Another difficulty is the lack of libraries and code available for this kind of architecture. This leads to two possible choices: the first is the development of a completely new library optimized for the ARM architecture and the second consist in "fitting" a library already available for x86 architecture. For the development of Eracle project we have chosen the last solution, as the aim of this project is not to build a basic library for ARM processors, but to realize a gesture recognition system. Some details among the adaptation of a mathematical library for ARM architecture are discussed in section 6.1.

To use the devkit it is necessary to install an appropriate OS on the board, this operation is usually called "flashing".
There are mainly two operative systems that can be flashed on the devkit: windows CE or Android (see section 2.2.2 for more information

concerning these OS). The appropriate msi file (it depends on the OS of the host PC) can be downloaded from the provided page on Tegra developer site [16], where it is also possible to retrieve some useful tools and demos. It is important to point out that almost all the provided support and examples are referred to Android.
Once the installation procedure is complete, a fully functional OS is available on the devkit; this feature makes the application development easier than in devices like PIC and DsPIC.
Once the OS has been installed it is possible to develop software applications directly on the host pc and deploy them directly to the devkit. For Windows CE the best choice is to develop a smart device application using Microsoft Visual Studio; to realize software that runs on Tegra, it is necessary to install the Standard Software Development Kit (STANDARDSDK_500) for Windows CE on the host pc. This package provides support for ARM4 and other mobile processors.

Tegra development board supports only a subset of .Net Framework, called .Net Compact Framework; it is a mobile-oriented environment mainly designed for mobile devices such as PDA, pocket PC, mobile phones and embedded processors. .Net Compact Framework offers these main functionalities:

- it provides an abstraction layer for executable files, making the executable code independent of the specific hardware platform;
- it supports the most common network protocols and offers facilities for handling connections with XML Web services;
- it provides a template for code development that is specific for smart device applications;
- it offers some optimizations related to the limited resources of the mobile systems.

The main advantage in developing an application on the devkit is that it is simply created as a Windows program. It means that the programmer doesn't care about the specific underlying hardware platform, but he can write his code in pure C++ using all the structure provided by this programming language.
Moreover, the Visual Studio Wizard already provides the main functions and classes required for a Windows application (such as the WinMain and WndProc functions, that handle the main message loop).

Furthermore, Visual Studio offers a wide suite of mobile devices emulators, that provide a software interface that is identical to the real device (see figure 5.3) allowing the developer to check the behavior of his executable file without deploy it to the physical device (although with worse performance than in the real case). The main constraints

Figure 5.3: A pocket PC emulator, that provides the same functionalities of a "real" Pocket PC

in developing Windows applications for a smart device is related to the use of .Net Compact Framework that doesn't support all the features of the complete .Net Environment; for example the compact version of CLR is about 12% of the complete edition and some mathematical methods and libraries are not available for all platforms. Another advantage in using the devkit with Visual Studio is that the executable file can be deployed directly to the board just by connecting the devkit to the host PC with a mini-USB cable. This avoid the use of a programmer, that is essential in programming microcontroller or PIC.

The main drawback in developing for Tegra CPU is the difficulty in reusing the already written code. The problem is mainly related with libraries for mathematical computation. Finding an implementation of such algorithms that can be executed on ARM architecture is a difficult

task.
One clear example of this problem is the Boost library ([6]), which is one of the best choices for mathematical computation algorithms: even if it is fully written in C++, it is unavailable for ARM architecture. This is also the case with IT++ ([12]), an open source mathematical library that implements useful structure such as matrices, vectors and algorithms for signal processing (including FastICA).
Unfortunately these libraries are expressly developed for x86 architecture, thus, for using them on an ARM machine it is necessary to port or recompile them. Modifying such amount of code in order to make it executable on a system which is different from the original one is an arduous task. This difficulty is mainly due to the complexity and the dimension of such libraries, but also to the limitations in using the .Net Compact Framework instead of the complete version of this environment.
Moreover, even if these libraries are successfully compiled for ARM architecture, they performed badly with respect to their version for the original target machine. In some cases it is also necessary to remove some features that are incompatible with the ARM architecture or the .Net Compact Framework, with a lack of functionalities with respect to the original version of the library.
For more information about porting library on ARM architecture, see chapter 6, section 6.1.

5.2 Electromyography board

The aim of the EMG board is to provide the analog to digital conversion of biometric signals sampled from the forearm muscles.

As shown in the architecture depicted in figure 5.4 it can sample up

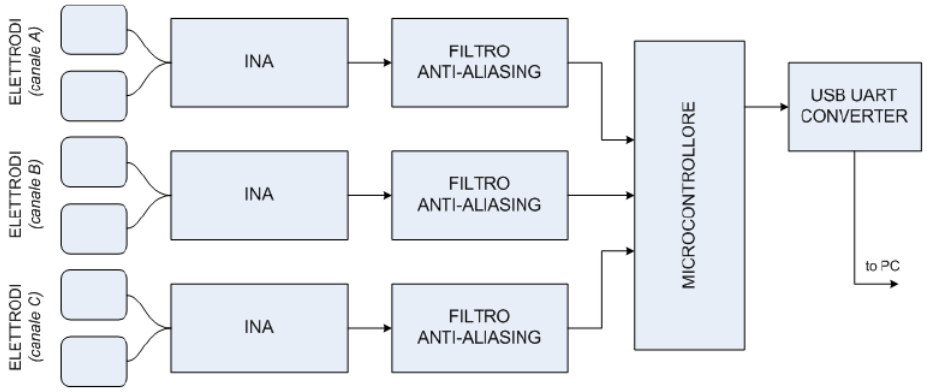


Figure 5.4: Architecture of the EMG board

to three different signals in differential mode. Each channel provides the following signal elaboration chain:

- once the signal have been sampled, it is processed by an INA amplifier, which provides an adjustable gain between 200 dB and 2000 dB;
- the next unit is a Sallen-Key anti-aliasing filter with double pole at 150 Hz;
- then the signal is processed by a PIC16F688 by Microchip ([14]), that provides the analog to digital conversion using a 10 bit ADC;
- at the end of the acquisition chain there is a FT232RL module that converts the communication from serial RS232 protocol to USB. This unit provides a communication speed of 57600 baud/s;
- thanks to a mini-USB output port is possible to connect this device directly to a PC; moreover - through the USB connection - it is also possible to power the whole board.

Due to its reduced dimensions (29 mm x 45 mm x 9 mm) and weight (35 g) the EMG board can be inserted inside the user's clothes without

hamper his movement. Figure 5.5 depicts the EMG board compared

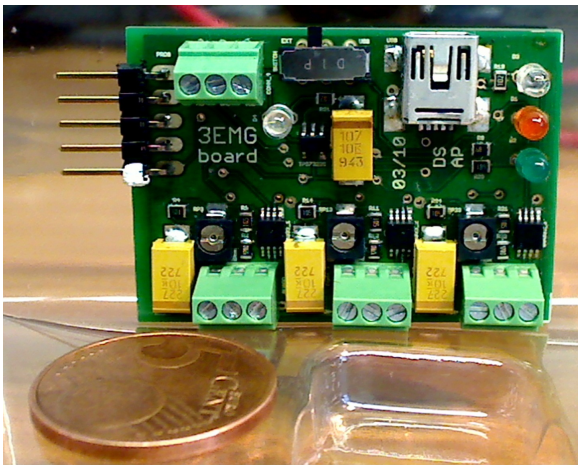


Figure 5.5: The EMG board compared to a 5 cent Euro coin

with a 5 Euro cent coin. The sampling rate of the board is of 270 samples/second.
An excerpt of the board output is listed below:

```
I:a b c
D:447 502 988
D:323 471 1011
D:327 834 816
D:220 666 567
D:438 519 530
...
...
...
I:a b c
```

The string *I:a b c* is repeated every 100 samples; the "D" character indicates the beginning of an acquisition, that consists in a digitalized value for every input channels.

5.3 FTDI interface

Future Technology Devices International ([11]) provides drivers to convert legacy peripherals (e.g. RS232) to Universal Serial Bus USB. Thus, thanks to FTDI it is possible to connect two (or more) devices with an USB cable, but the connection is simply managed as serial port communication. Such interface is also employed to extend the basic functionalities of standard COM port.
There are mainly two types of FTDI drivers:

- **VCP:** which provides only a virtual COM port on the target device;
- **D2XX:** that provides both a virtual COM port and some special features that are usually unavailable in standard COM port APIs. Thanks to these additional characteristics, it is possible to change the operating mode of a device, or to write data into an EEPROM.

These two drivers are merged in the Combined Driver Model package. Both these two interfaces are supported by the common FTDI bus which is directly connected to the USB controller managed by the OS. The architecture of FTDI Combined Driver Model for Windows systems is shown in figure 5.6.

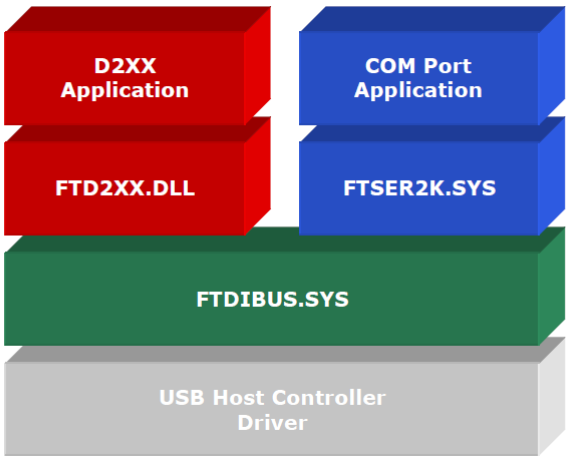


Figure 5.6: FTDI driver architecture for Windows

The two drivers can't be both installed on a Windows CE system, as they are mutually exclusive for this Operative System. FTDI interface is provided as a dll file that must be employed as a driver setup

file on the host pc when the external device is plugged.

In Eracle project, the VCP version of FTDI drivers has been employed, as we just need basic IO operations on a virtual serial port. This kind of interface makes possible to exchange data between the EMG board (described in section 5.2) and the devkit (described in section 5.1).
The EMG board can be connected with a USB-mini cable to the devkit, which retrieves the sampled data simple by opening a serial port as a file and reading the signal's digital values from it. In our case, the virtual serial port created by the FTDI interface is named COM10; this information can be retrieved by using the Remote Registry Editor available on the host PC.
The following code listing shows the main steps necessary to handle the serial connection and to retrieve the data acquired by the EMG board.

```
/*main variables for the serial port handling*/
  HANDLE hSer;
  DCB dcb;
  dcb.DCBlength=sizeof(dcb);
  dcb.BaudRate=57600;

/*variables for serial port reading*/
  INT rc;
  CHAR buffer [15000];
  DWORD bytesRead;

/*create a serial port handler*/
  hSer=CreateFile(TEXT("$device\\COM10"),
                  GENERIC_READ|GENERIC_WRITE,0,
                  NULL,OPEN_EXISTING,0,NULL);

/*set the COM port options*/
  GetCommState(hSer,&dcb);
  SetCommState(hSer,&dcb);

  PurgeComm(hSer,PURGE_TXABORT | PURGE_RXABORT
            | PURGE_TXCLEAR | PURGE_RXCLEAR);
```

```
/*read data from the COM port
and put them into the buffer*/
  rc = ReadFile(hSer,buffer,
                sizeof(buffer),&bytesRead ,0)

/*close the virtual serial port connection*/
  CloseHandle(hSer);
```

Chapter 6

Project development

> *" We are the Borg. You will be assimilated. Your biological and technological distinctiveness will be added to our own. Resistance is futile."*
>
> Star Trek VIII - First Contact

This chapter provides a detailed description of Eracle project.
As previously described in chapter 3, section 3.3, Eracle project consists of two different modules.
The first one is implemented on the Acquisition Glove that samples the EMG signals and converts them to digital values. The main sub-units of this module are:

- the **sEMG electrodes** that acquire the input signal from the user's skin;
- the **EMG Board** that converts the input EMG signals to digital values.

Section 6.2, provides some details about the Acquisition Glove.

The second module is fully developed on Tegra Devkit, it provides the data processing for the acquired signals and the gesture recognition engine. It consists of two different executable files: EracleACQ, that provides the training stage for the classifier, and EracleREC that identifies the gesture performed by the user. The sub-units of this module are:

- a **Serial Port Manager** that handles the communication between Devkit and EMG Board;

- the **Parser** unit, that split the input data into three different listings (one per channel) and erases the spurious data;
- the **FastICA** unit that processes and filters the raw input data;
- a **RMS** unit that computes the Root Mean Square value for each channel;
- the **NN Train** module that trains the Multi Layer Perceptron that will recognize the user's gestures;
- the **NN Classify** unit, that classifies the user's gesture employing the previously trained Neural Network.

The last unit is implemented only in EracleREC, while the *NN train* module is developed only on EracleACQ. Section 6.3, provides some details about all the modules implemented on the Devkit.
Both the FastICA module and the Neural Network units are developed using some features of LTIlib, a C++ library mainly employed for image processing. The first section of this chapter provides some details about LTIlib and how it has been recompiled for ARM architecture.

6.1 LTIlib

LTIlib is an open-source library that provides some basic data types and algorithms commonly employed in image processing and computer vision; it is fully developed in C++ language. The project is carried out by the Chair of Technical Computer Science at the Aachen University of Technology.
Unlike other mathematical libraries (e.g. IT++ or Boost), LTIlib is self-contained, thus it doesn't require any library that supports the basic mathematical or algebraic operations. In Eracle project, LTIlib provides some mathematical structures and algorithms mainly employed in *FastICA, NN Train* and *NN Classify* modules of the computing core (see figure 6.1).

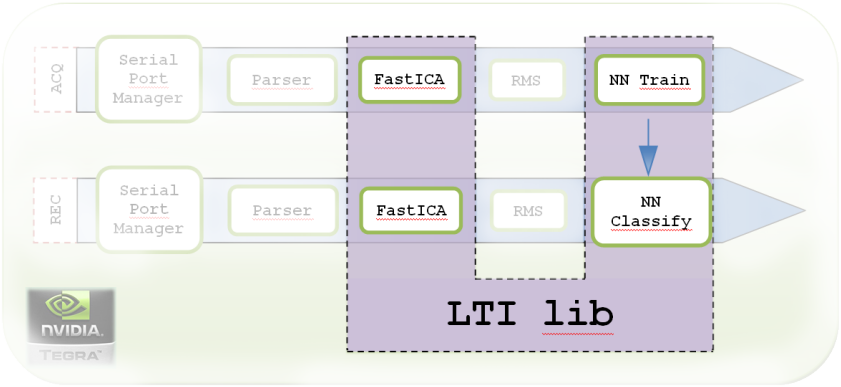


Figure 6.1: LTIlib structures and algorithms are mainly employed in FastICA and Neural Network modules of Eracle's computing core

6.1.1 Architecture of LTIlib

LTIlib provides both data structures (matrices, vectors, tensors...) and algorithms. Both these two features can be classified in one of the following classes:

- **linear algebra:** it provides matrices, vectors, and functions to extract eigenvalues, eigenvectors and to solve linear equations;
- **classification and clustering:** it provides classifiers like Neural Networks, Support Vector Machines and Fuzzy C-Means clustering algorithm;

- **Image processing:** this class provides wavelets, linear filters and other algorithms that deal with image processing problems;

- **Visualization and drawing tools:** these classes provide the viewer objects to display or manipulate an image.

The architecture of LTI library is really simple and it is based on three main entities: **functors, parameters and states**.

- **Functors**
  Functors are classes containing all the functions of an algorithm. Every functor class contains at least one *apply* method that executes the algorithm on the source data provided .
  Consider a Multi Layer Perceptron Neural Network as an example: the object that represents the classifier is a functor.

- **Parameters**
  One instance of this class is encapsulated in every functor, as it provides the specifications of the algorithm. The user can set this values by using the *setParameters* method related to the functor class. It is also possible to employ the default parameter class initialized when the functor class is declared.
  Examples of parameters in a Neural Network are: the number of epochs, the number of neurons in the hidden layer and the value of the learning rate.

- **States**
  States are attributes that are computed during the algorithm's execution, but that aren't required by the user.
  Considering the NN example, a state is the number of weights computed during the training stage, that isn't explicitly defined by the user but is computed by the training algorithm.

The main advantages in using these three different entities are: first of all the behavior of the algorithm is independent of its parameters, thus the functor is completely uncorrelated from the input data and it implements only the functionality of the procedure; secondly this is a general interface that can be applied to every algorithm, simply overloading the *apply* methods that executes the algorithm.
Figure 6.2 depicts the general architecture of LTIlib.

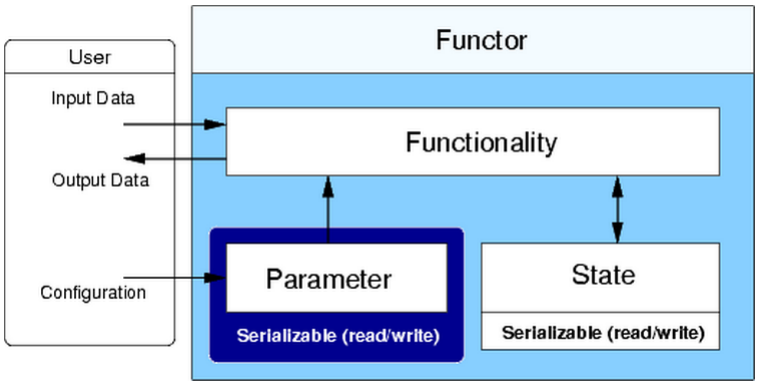


Figure 6.2: General architecture of an LTILIB class: the functor is the general structure that contains both the algorithm and its options. The user sets the desired configuration with parameters. States and Parameters implement the desired functionality of the algorithm.

6.1.2 Recompiling LTIlib

One of the main disadvantages in using the Devkit described in chapter 5 is the lack of libraries available for ARM architecture. Thus, a developer has two possible choices: he could write from scratch the functions and the structures he needs, or he could try to recompile an existing library.
In Eracle project we mainly need structures, like matrices and vectors, algorithms, like FastICA and classifiers, like Multi Layer Perceptrons. As these features are already available in some open-source libraries and there are some difficulties in writing them from scratch, we've decided to convert an existing library to ARM architecture.
We have identified three libraries that could be suitable for our purpose: Boost, IT++ and LTIlib. We have failed in recompiling Boost and IT++, mainly because they are not self-contained, but they are based on other libraries that provide optimized computing algorithms. For example, IT++ libraries are more powerful than LTIlib, as they manage matrices and vectors in a simpler way, moreover they offer a wide selection of algorithms; unfortunately, IT++ libraries require BLAS and LAPACK to handle basic mathematical and algebraic structures with the related operations. Recompile three libraries for ARM architecture is a more difficult task than recompile only one.

LTIlib provides less powerful features and less optimizations than IT++ or Boost, but it is self-contained and more easy-to-handle, as it is written in "pure" C++ code. Thanks to these features it has been successfully recompiled for ARM architecture.
To recompile LTIlib for ARM architecture we have adopted two main approaches:

- if the problematic feature is related to visualization, or to some algorithms that are useless for our project, the corresponding code is simply commented;
- in the other cases, the problematic code has been rewritten or adapted.

Not all the features have been retained. First of all it has been necessary to remove all the references to GTK libraries that are employed for image visualization. To achieve this result, some preprocessor directives that configure GTK as standard visualization tool have been deleted.
Another change is related to optimized assembly operations. It is a common case that mathematical libraries implement some functions directly in assembly: unfortunately, x86 assembler (the target CPU of LTIlib) is different from ARM assembler. To avoid this problem, the assembly functions have been replaced with less optimized C++ instructions.
Some preprocessor directives have been modified to be executed on Windows CE, which is not the target OS of LTIlib.
Other changes involve the header files provided with STANDARDSDK_500. Some of these files don't contain all the elements and declarations required by LTIlib. For example, the header file stat.h provided with STANDARDSDK_500, requires some additional definitions such as:

```
typedef unsigned int _dev_t;
typedef unsigned short _ino_t;
typedef long _off_t;
```

It is important that the include paths are set in an appropriate way: they must be referred to the include files specifically provided for Windows CE and to the STANDARDSDK_500 path.

Some changes consist in pure casting operations, such as the following one, in which the file name has been converted to LPCTSTR type:

```
//before...
   if(!DeleteFile(fileName))

//... and after
   if(!DeleteFile((LPCTSTR)fileName))
```

Another important change regards threads and the process management routines implemented in LTIlib. These two features provide functions like *fork* and *exec* employed in UNIX environment, but they lead to compilation error, so these feature has been removed.
At the end of this procedure a static library has been achieved, that can easily be linked at compile time with the source code developed in C++. Some modifications has been also necessary in Visual Studio, such as enables the Run Time Type Information (RTTI) option.

6.2 Acquisition glove

The acquisition glove is the input device of Eracle project.
It provides support both for the surface EMG electrodes and the EMG Board, as shown in figure 6.3. The main advantage in using a glove is

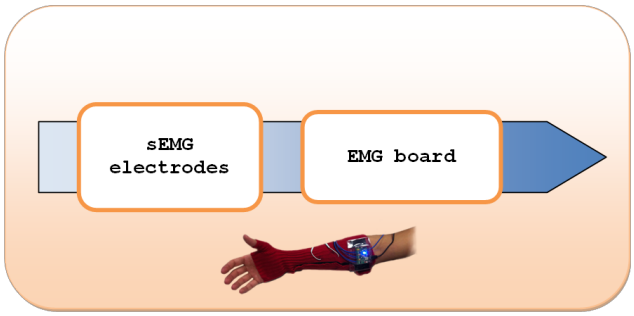


Figure 6.3: The acquisition glove contains both the surface EMG electrodes and the EMG Board that provides analog to digital conversion of the sampled signals.

that it ensures (or at least eases) the repeatability of electrodes placement. Thus, if some time elapses between the training phase of the system and the recognition stage, we must be sure that the electrodes positions are about the same or the output results will be unreliable.
The main drawback in using a glove that encloses the whole forearm is the temperature rise that mainly causes these difficulties ([52]):

- the signal latency is prolonged (0,2 ms/°C);
- the amplitude and the length of EMG signal are increased;
- the impedance of the electrodes is increased.

Thus, if the user wears the glove for too long, the sampled EMG signals are distorted.
Since the glove could be worn by people with different physique, the final version will be realized with elastic material.
Figure 6.4 depicts a prototype of the acquisition glove. The electrodes employed on the acquisition glove are commercial equipment of 40 mm x 40 mm or 50 mm x 50 mm with an impedance of approximately 10 MΩ. This last value is provided only as a rough guide, since it widely depends on physical parameters of the user (like weight or sweating) and on general electrodes condition.
In general, larger electrodes entail more noisy signals, mainly due to

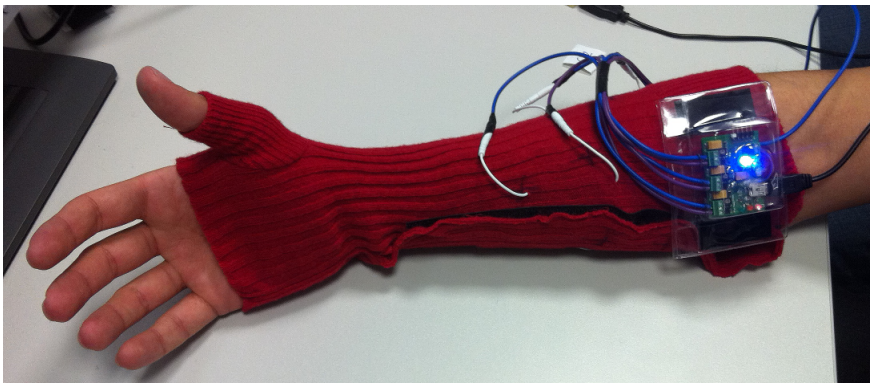


Figure 6.4: Prototype of the acquisition glove. The wires came out from the electrodes placed on the user's skin. They are connected to the EMG Board that is hooked to the glove with Velcro strips.

crosstalking. An example of a commercially available electrode suitable for EMG acquisition is shown in figure 6.5. These sensors are not designed for a prolonged use and their surface degrades quickly, this leads to an increase in signal's noise and in a lack of recognizer's performance. As the aim of the project is to recognize the hand movement,

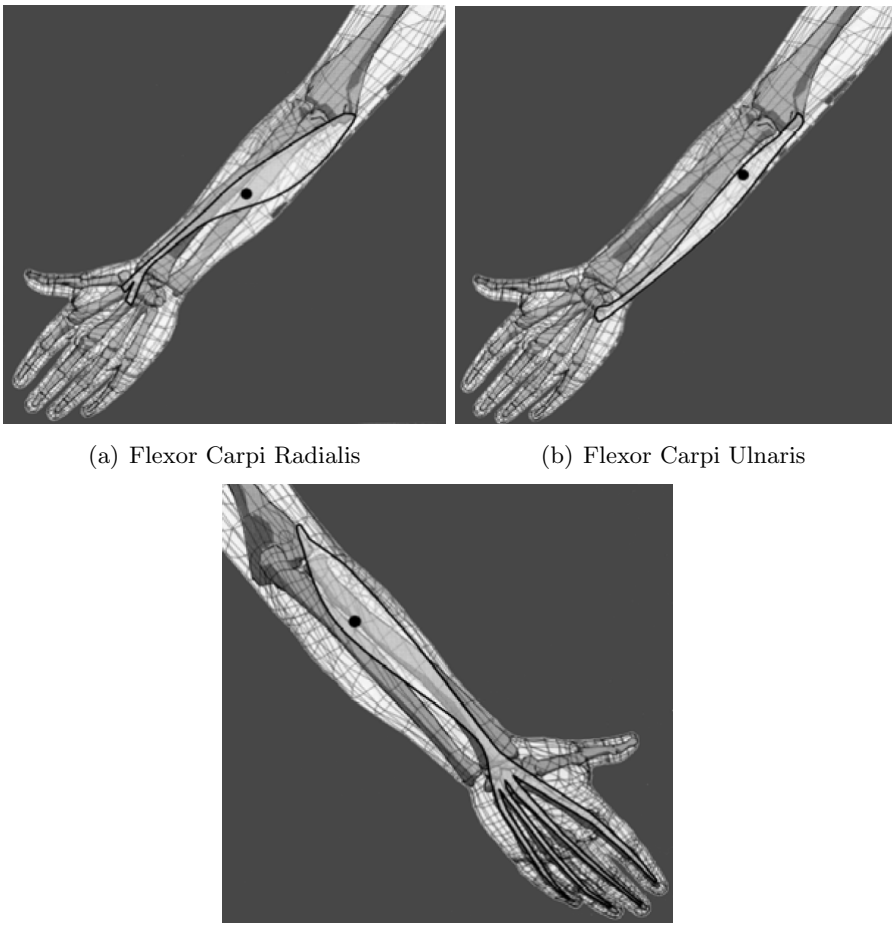
Figure 6.5: Example of commercially available electrodes suitable for EMG acquisition. They are usually employed for electro stimulators

the electrodes must be placed on the appropriate muscles of the forearm. The acquisition glove shown in figure 6.4, provides three couples of electrodes and a reference that must be applied on the elbow.
The electrodes must be placed in couples, as each channel is sampled in differential mode.
As described in [52], the three muscles that are involved in the five

hand movements recognized by Eracle are:

- **Flexor Carpi Radialis** - it takes part in flexion and abduction of wrist;
- **Flexor Carpi Ulnaris** - it takes part in flexion of wrist;
- **Extensor Digitorum Comunis** - it takes part in fingers flexion and extension.

The placement of the three couples of electrodes is shown in figure 6.6. The electrodes are connected to the EMG board that provides the



(a) Flexor Carpi Radialis (b) Flexor Carpi Ulnaris

(c) Extensor Digitorum Comunis

Figure 6.6: Placement of the electrodes for EMG acquisition [52]

analog to digital conversion of the sampled signals. This device has already been widely described in section 5.2, however, it is important

to point out that - due to its reduced weight and size - the EMG board can be easily integrated in the acquisition glove, as shown in figure 6.4. This feature makes possible to realize a fully wearable interface that is easy to wear and use. Moreover, mainly due to the reduced weight of the whole system, it doesn't hamper the user's movement, allowing a natural execution of the gestures.

6.3 Tegra modules

Once the EMG signals have been converted to digital values (with the conversion specifications described in section 5.2) the sampled data are processed in order to obtain both the training examples for the neural network (EracleACQ) and the classification data (EracleREC).
The whole computing core of Eracle has been developed on Tegra Devkit (described in chapter 5, section 5.1) and it is depicted in figure 6.7.

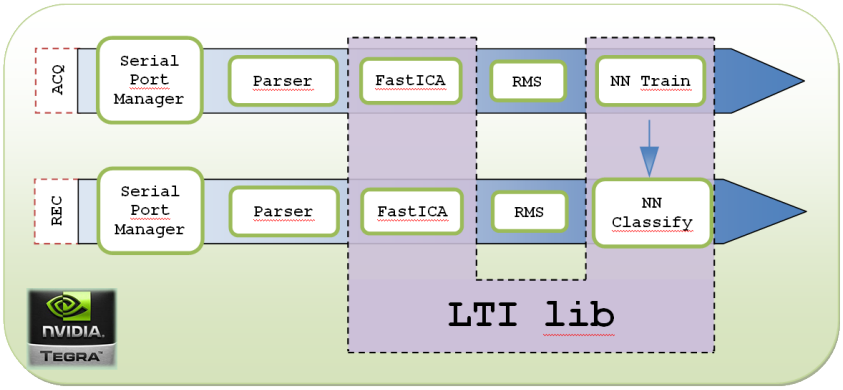


Figure 6.7: Two different executable files have been developed on Tegra Devkit. EracleACQ provides the units for the training stage of the classifier (serial port manager, parsing, FastICA, RMS and NN train); EracleREC provides about the same modules but they are optimized for the recognizing stage of the classifier.

6.3.1 Serial port manager

The first module designed for data processing is the serial port manager.
This unit opens a connection toward the EMG board through a virtual COM port. The virtual serial port is provided thanks to the VCP FTDI driver previously described in section 5.3. The output data of EMG board are received by reading a file; the retrieved samples are placed in a CHAR buffer of 15000 elements. The buffer's size is not a random number, but it is defined in order to acquire the EMG signals for 3/4 seconds; however, we think that the sampling time could be reduced without any lack of performance (see chapter 8, section 8.1). This acquisition time corresponds to 1050/1060 samples for each channel.

Once the user has performed the movement, the sampling is stopped, the virtual COM port is closed and the data held in the CHAR buffer are written on a file for succeeding processing. The output files look like the excerpt listed below:

```
 501 509
D:508 509 512
D:508 507 511
D:512 501 511
D:505 507 500
...
...
...
D:498 519 504
I:a b c
D:508 504 517
D:509 507 511
D:511 5
```

The acquisition procedure is repeated until all the acquisition have been performed.
The C++ code that handles data acquisition from the EMG board is listed in appendix A, section A.1. The previous listed output is the most general one achievable from the EMG board. There are some spurious data both at the beginning and at the end of the file, moreover - as already described in section 5.2 - every 100 samples the string *I:a b c* is added to the output list.
The next unit deals with such spurious value in the input data.

6.3.2 Data parsing

Once the input data have been acquired from the EMG board, it is necessary to process them, removing any spurious value. It is also necessary to split the original input file in three different sources before processing them with FastICA algorithm. In particular, this unit performs the main tasks outlined in figure 6.8. Before processing the input data it is useful to copy the whole contents of the input file to a STL container like a string. On this kind of data type it is possible to employ some functions of the Standard Template Libraries, like *find* or *replace*.

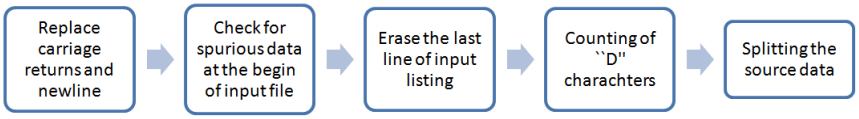


Figure 6.8: The main tasks performed by the parsing module

Replace carriage returns and newline

This task can easily be accomplished thanks to the *replace* method implemented in the STL *Algorithms*. For example the following instruction replaces all the occurrences of newline character with space character in the STL container tot:

```
replace(tot.begin(), tot.end(), '\n', ' ');
```

Check for spurious data at the begin of input file

The next step consists in checking if there are some spurious data at the beginning of the input file. This check can easily be performed by finding the first occurrence of "D" character and by retrieving its position in the container; if the index number is equal to zero, it means that the input file correctly begins with a "D", thus there are no partial data at the top of the file. Otherwise - if the retrieved index is different from zero - it means that all the characters before the index position must be erased, as they are part of an incomplete samples.
The following code performs the previously described algorithm:

```
//find the position of the first D
  posD=tot.find("D");

//if file doesn't begin with D...
  if(posD!=0){

//... erase all characters before D
    tot.erase(0,posD);
  }
```

Erase the last line of input listing

This operation is necessary to prevent spurious data at the end of input file.
As we acquire more samples than necessary, it doesn't matter if one sample vector is deleted.
To perform this task it is necessary to retrieve the positions of the last "D" character and of the termination character "/0", then all the values between these two indexes are erased.
The following listing performs the described task:

```
  size_t ultimo;
  size_t fine;

//get the position of last D...
  ultimo = tot.rfind("D");

//... and the position of the termination char
  fine = tot.rfind("\0");

/*delete last row,
but don't erase "\0" character*/
  tot.erase(ultimo, fine-1);
```

This procedure could be optimized by avoiding the erasure of the last input vector if it is a complete sample. This can easily be performed by finding the last "D" and then counting the number of spaces before the termination character. If the number of spaces is less than three, it means that the sample is not complete and then it must be erased.

Counting of "D" characters

This procedure is not strictly necessary, but it is useful for error checking.
Some experiments and some observations about the maximum memory load of the Devkit lead us to the considerations that 1010 samples are widely acceptable for performing movement recognition. This entails that if (for any reason) the system obtains less than 1010 samples for each channel, the acquisition procedure is invalid and must be aborted. This check can easily be performed by counting the occurrences of "D"

characters in the input file and ensuring that they are greater than 1010. Moreover, it is necessary that all the channels contains exactly the same number of samples to avoid errors in the following FastICA processing.
The following code listing implements these considerations:

```
//numbers of "clean" data acquired
  int counter = count(tot.begin(),tot.end(),'D');

  if(counter<1010){
    MessageBox(NULL, TEXT("Few samples"),
               TEXT("EracleParser"), MB_OK);
    exit(0);
  }
```

Splitting the source data

The last section is the core of this unit: it splits the source data into three different source files: one for each channel.
The main idea of the algorithm is as following:

- find the first "D" character and retrieve its index (the position of the first one is surely zero, due to the second step previously described);
- retrieve the position of the first space;
- copy the characters between the two indexes in the first channel destination file;
- starting from the first space find the second one and save its index;
- copy the characters between the two indexes in the second channel destination file;
- starting from the second space find the last space in the triple (that always exists due to previously described steps one and three);
- copy the characters between the two indexes in the third channel destination file.

This procedure is repeated until all the sampled triples have been splitted.
The result consists in three files filled with the sampled values, each sample is separated only by a white space.
The code that implements this last functionality is quoted in appendix A, section A.2.

6.3.3 Fast ICA module

The third unit implements FastICA on the Devkit. The principles and the purpose of this algorithm have already been discussed in 4. For each movement repetition, this unit performs the tasks depicted in figure 6.9. First of all it is necessary to compute the average value

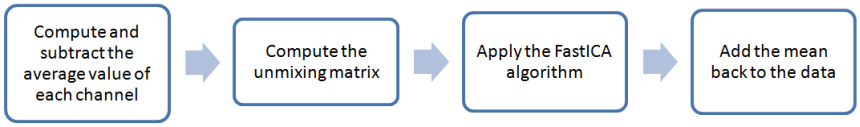


Figure 6.9: Main tasks performed by the FastICA module

for each of the three input channels, then this value is subtracted from each samples of the corresponding source. The following C++ code shows how to implement this functionality:

```
/*the array that will contains
the mean values*/
  double mean[3];
  double temp=0;

/*compute the average value
of each source channel*/
  for(int j=0;j<3;j++){

    for(int i=0; i<DIM_CHANNEL; i++){
      temp = temp+sourceT.at(i,j);
    }

    mean[j]=temp/DIM_CHANNEL;

  temp = 0;
  }

/*it is necessary to define a matrix
containing the mean values to subtract
them from the whole dataset*/
```

```
    lti::matrix<double> media(1,3,mean);

    const double init =1;
    lti::matrix<double> ones(DIM_CHANNEL,1,init);

    lti::matrix<double> matmedia;

    matmedia.multiply(ones,media);

  /*subtract average values from
  the whole dataset*/
    sourceT.subtract(matmedia);
```

Then the ICA algorithm is applied, it separates the source signals that are overlapped due to the crosstalking between the forearm muscles.
It is important to point out that the unmixing matrix is computed for every movement repetition, thus for each element of the dataset. This choice is in contrast with what has been proposed by Naik et al in [43], as they compute the W matrix only with the first set of samples and then it is applied to the other repetitions of the same movement. This choice is unsuitable for Eracle project mainly for two reasons:

- computing the unmixing matrix considering only the first set of data makes the whole system too much sensible to the quality of this sample, thus if the first acquisition is performed badly, it will invalidate all the training process.
- in the project described by Naik in [43], the data employed for training and classification are sampled at the same time, thus during the same session. In Eracle the user can train the device and use it for recognition in completely different times.

So the W matrix can't be constant, as it is different for each movement, and selecting the more appropriate one before starting the recognition procedure would entail that the device already knows the gesture that the user will perform.
FastICA algorithm is a feature available in LTIlib and it can be applied as stated in the following code excerpt:

```
  //FastICA object
    lti::fastICA<double> ica;
```

```
//unmixing matrix
  lti::matrix <double> unMat;

/*apply the ICA algorithm to the data
saved in source matrix.
Result is stored in clean matrix*/
  ica.apply(source,clean);

//print the transformation matrix
  ica.getTransformMatrix(constTransfMatrix);
```

The last step consists is adding the mean back to the data, more precisely it applies the following formula to the output values of FastICA algorithm:

$$output = W \times unMixedSignal + (W \times mixedMean) \times ones(1, NumOfSamples)$$

where:

- W is the unmixing matrix computed by ICA;
- *unMixedSignal* is the matrix filled with the output data of FastICA algorithm;
- *mixedMean* is the vector containing the average values of the source data;
- *ones(1,NumOfSamples)* is a vector with number of columns equal to the number of samples acquired, filled with the number one.

The following code listing implements the described equation:

```
//first member of equation
  lti::matrix<double> first;

/*((1))first = W*unmixedsig*/

/*unMixedSignal matrix must be transposed
in cleanT to be multiplied*/
    lti::matrix<double> cleanT;
    cleanT.transpose(unMixedSignal);
    first.multiply(constTransfMatrix,cleanT);
```

```
/*((2))v=W*mixedMean*/
    lti::vector<double> v;
//retrieve the mean of input data
    ica.getOffsetVector(v);
    W.multiply(v);


/*v must be transposed to compute
the last multiply (but there's no tranpose
method for vectors in LTILIB)*/
    double temp[3];
    for(int h=0;h<3;h++){ //"homemade" transpose
      temp[h]=v.at(h);
    }


/*tempMat = (W * mixedmean)
as in LTILIB doesn't exists a column vector,
a 3x1 matrix is employed*/
    lti::matrix<double> tempMat (3,1,appoggio);



/*((3))a matrix filled with ones,
in MATLAB it would be:
ones(1,numOfSamples)*/
    const double inival =1;
    lti::matrix<double> ones(1,DIM_CHANNEL,inival);



/*((4))second = tempMat*unii
    lti::matrix<double> second;
    second.multiply(tempMat,ones);
```

```
/*((5))output = first + second*/
    lti::matrix<double> output;
    uscita = primoMembro+secondoMembro;
```

This operation (as well as the average value subtraction described as first step of this unit) has been suggested by the Matlab implementation of FastICA algorithm proposed by Hyvärinen ([33]) and developed by the Laboratory of Computer and Information Science of the Helsinki University of Technology ([10]). Moreover - as described in chapter 4, section 4.3.2 - FastICA requires some preprocessing operations, in order to be correctly applied.
The introduction of such changes in the standard FastICA algorithm provided by LTIlib improves the recognizer accuracy of at least 30%. Chapter 7 reports some experimental results achieved with and without this modification. The complete code listing of these modules is quoted in appendix A, section A.3.

6.3.4 Root Mean Square

The main function of this unit is to "summarize" the results obtained in the previous module with ICA application.
Root mean square can be defined as a value that concisely represents the muscle activity for each source channel([43]). Some experimental results show that RMS value is higher when the corresponding muscle is less contracted and vice versa.
Root Mean Square is computed using the following formula:

$$RMS_i = \sqrt{\frac{1}{N}\sum_{i=1}^{N} s_i^2} \quad (1 \leq i \leq 3) \tag{6.1}$$

where N is the number of samples for each channel (1010).
This equation can easily be translated in C++ language as:

```
double RMS;
double sumOfSquare=0;

//compute RMS for each of the three channels
for(int ch=0; ch<3;ch++){

  for(int k=0;k<DIM_CHANNEL;k++){
```

```
        sumOfSquare=sumOfSquare +
                    pow(clean_source.at(ch,k),2);
    }

    RMS = sqrt(sumOfSquare/DIM_CHANNEL);

    RMS=0;
    sumOfSquare=0;
}
```

where DIM_CHANNEL is a constant value that defines the number of samples for each channel.
It is computed for each channel for every movement repetition; thus, if the user performs 20 movements, we obtain 60 RMS values. These data are saved in a file according to the pattern: RMS_{ch1}rep1 RMS_{ch2}rep1 RMS_{ch3}rep1 ...
The RMS values obtained from the repetitions of the same movement are stored in a file whose name identifies the movement performed by the user. The indexes that identify the performed movement depend on the number of gestures that the device will recognize. For the final prototype of Eracle, we've proposed the five gestures described in chapter 3, section 3.1, which are:

- **close hand:** which corresponds to index 0;
- **wrist extension:** which corresponds to index 1;
- **wrist flexion:** which corresponds to index 2;
- **open hand:** which corresponds to index 3;
- **click:** which corresponds to index 4.

For example, all the RMS computed for every repetition of the gesture "close hand" are saved in a file named *RMSmov0*.
The complete code listing can be found in A, section A.4.

6.3.5 NN trainer

The last module of EracleACQ provides the training stage for the Neural Network that will recognize the user's gestures.
More precisely, this unit performs the tasks outlined in figure 6.10. An excerpt of

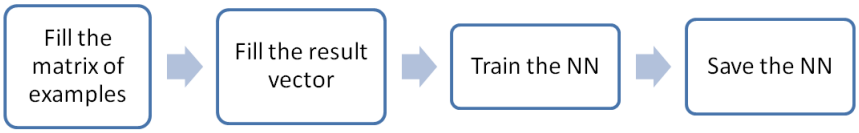


Figure 6.10: The main tasks performed by the Neural Network Train module

dataset employed in training stage is stated in table 6.1:

Gesture	Channel 1	Channel 2	Channel 3
Close hand	9,846	9,053	8,763
	9,833	7,675	7,408
	8,303	8,224	7,087
	9,589	6,789	4,843
	9,685	6,978	6,1623
Wrist extension	33,274	5,188	16,283
	35,861	5,415	8,717
	29,897	4,789	7,049
	27,923	4,473	14,026
	29,053	4,090	13,411
Wrist flexion	15,871	13,528	4,513
	14,675	11,895	3,789
	18,899	19,002	3,123
	13,298	12,213	3,852
	18,911	19,050	3,369
Open hand	15,125	6,750	16,249
	17,146	6,926	10,424
	15,765	7,321	13,237
	16,765	7,543	16,145
	15,072	7,369	15,992
Click	31,381	25,113	24,882
	33,406	22,160	17,528
	31,049	25,563	16,942
	45,506	34,092	22,190
	29,783	23,464	24,840

Table 6.1: An excerpt of RMS values employed for training and recognition

The stated RMS can be roughly divided in three clusters:

- **low** if $RMS \leq 67$;
- **medium** if $7 \leq RMS \leq 19$
- **high** if $RMS \geq 20$;

Looking at the RMS stated in the previous table it is possible to identify five different patterns, one for each movement: Just by looking at this roughly classification

Gesture	Channel 1	Channel 2	Channel 3
Close hand	*medium*	*medium*	*medium*
Wrist extension	*high*	*low*	*medium*
Wrist flexion	*medium*	*medium*	*low*
Open hand	*medium*	*low*	*medium*
Click	*high*	*high*	*high*

Table 6.2: RMS patterns of the five gestures recognized by Eracle

it is clear that some patterns are more likely to be confused than others. For example, the only difference between *wrist extension* and *open hand* is in channel 1, that has a high value in the first gesture and a medium amplitude in the second one. This aspect will be further investigated in the next chapter, section 7.2.

Fill the matrix of examples

To train a Neural Network it is necessary to provide a matrix with the input data examples. These examples are the RMS values computed at the previous step.
As every movement is repeated NUM_ACQ times, the input matrix has a dimension of NUM_ACQ*NUM_GESTURE rows and 3 columns (NUM_GESTURE is the number of recognized movements). Before filling the matrix it is necessary to create an array of double that stores the computed RMS, according to the pattern reported in the previous section. The matrix constructor - that builds the object we need - and the algorithm that fills the array of double with the appropriate RMS values are quoted below:

```
//examples data array for training
  double RMSglobal [((NUM_ACQ)*NUM_GESTURE)*3];

//fill each input vector with data from corresponding file

//((NUM_ACQ)*3) RMS for mov0
  for(int k=0;k<((NUM_ACQ)*3);k++){
    fscanf(mov0, "%lf", &RMSglobal[k]);
  }
```

```
//((NUM_ACQ)*3) RMS for mov1
  for(int k=((NUM_ACQ)*3);k<(((NUM_ACQ)*3)*2);k++){
    fscanf(mov1, "%lf", &RMSglobal[k]);
  }

//((NUM_ACQ)*3) RMS for mov2
  for(int k=(((NUM_ACQ)*3)*2);k<(((NUM_ACQ)*3)*3);k++){
    fscanf(mov2, "%lf", &RMSglobal[k]);
  }

//((NUM_ACQ)*3) RMS for mov3
  for(int k=(((NUM_ACQ)*3)*3);k<(((NUM_ACQ)*3)*4);k++){
    fscanf(mov3, "%lf", &RMSglobal[k]);
  }


//matrix filled with training data
  lti::dmatrix train_matrix (NUM_GESTURE*NUM_ACQ,
                             3,RMSglobal);
```

Fill the results vector

The next step consists in filling a vector with the indexes that correspond to the performed gestures. As every movement is repeated NUM_ACQ times this vector has a size of NUM_ACQ*NUM_GESTURE. This array provides the "answers" to every data set analyzed by the NN during the training stage. Thanks to the data type available in LTIlib it can be implemented as follows:

```
//answer data array for training
  int RMSanswer [NUM_ACQ*NUM_GESTURE];

/*fill the array that provides
input data for answer vector*/

//NUM_ACQ rms represents mov0
  for(i=0; i<NUM_ACQ; i++)
    RMSanswer[i]=0;

//NUM_ACQ rms represents mov1
  for(i = NUM_ACQ; i<NUM_ACQ*2;i++)
    RMSanswer[i]=1;

//NUM_ACQ rms represents mov2
  for(i = NUM_ACQ*2; i<NUM_ACQ*3;i++)
    RMSanswer[i]=2;
```

```
//NUM_ACQ rms represents mov3
  for(i = NUM_ACQ*3; i<NUM_ACQ*4;i++)
    RMSanswer[i]=3;

//the results vector employed for training
  lti::ivector train_results_vector (NUM_ACQ*NUM_GESTURE,
                                     RMSanswer);
```

Neural network training and save

The most important operation performed by this unit is the training of the Neural Network.
LTIlib provides three main classes of Artificial Neural Network that can be employed for data classification:

- **Multi-Layer Perceptron**
- **Learning Vector Quantization**
- **Radial Basis Function Network**

In Eracle project the first kind of network has been employed, this choice has been dictated mainly by two reasons: the first one is that multi-layer Perceptron (MLP) are the most widely used Neural Network classifiers, as they are easy to use and flexible (compared with other architectures); secondly, LTIlib provides more supports and features for MLP with respect to other architectures like Radial Basis Networks.

Declare a MLP with LTIlib is a simple task; the hard part of using a NN consists in defining the net's parameters, such as:

- the number of **training epochs;**
- the number of **neurons in the hidden layer;**
- the **activation function** of the neurons;
- the **training algorithm;**
- the value of the **learning rate;**
- the **number of examples** that are presented to the NN during the training stage.

With LTIlib it is possible to set all the listed parameters (as well as many other like the *momentum factor*). The following code excerpt shows how to declare a MLP and how to set some basic parameters (for more information about LTIlib parameters see section 6.1):

```
//object NN
  lti::MLP ann;

//NN parameters set-up
  lti::MLP::parameters param;
  lti::MLP::sigmoidFunctor sigmoid(1);
  param.setLayers(12,sigmoid);
  param.trainingMode=lti::MLP::parameters::SteepestDescent;
  param.maxNumberOfEpochs=2000;
  param.learnrate=0.01;
  ann.setParameters(param);
```

These settings defined a MLP with the following features:

- each neuron has a sigmoid activation function with a slope factor of 1.0;
- there are 12 neurons in the hidden layer;
- the employed training algorithm is Steepest Descent (Generalized Delta-Rule);
- 2000 training epochs;
- learning rate of 0.01

The number of neurons in input and output layers is determined by the dataset size.
As described in chapter 7, section 7.2, the quoted Neural Network is able to recognize up to five different gestures with an average performance of 90%.
Once the NN has been set, it can be trained and saved; then it can be employed for classification. The train of the MLP consists in the following simple line of code:

```
ann.train(train_matrix,train_results_vector);
```

where *ann* is the MLP object, *train_matrix* and *train_result_vector* are the matrix of the input example and the corresponding answer vector previously described.
It takes some times to train the network: the length of this task depends on its settings. For the Multi Layer Perceptron quoted in the previous listing, the training time is between 10s and 15s.
Once the training stage has been completed, the network is saved in a .dat file, ready to be employed in the recognition procedure.
The complete code of this unit is listed in appendix A, section A.5.

6.3.6 NN classifier

This unit is the last step of the recognition procedure, and it is implemented only in EracleREC. The main task of this module is to recognize (by using the previously trained NN) the user's gestures.
This module receives as input the RMS generated by one single user's movement, then it opens the previously trained NN and tries to recognize the user's gesture.

Open the previously trained NN is a simple task, due to the lispStreamHandler provided by LTIlib; it is an interface for LTIlib classes to read and write them in a LISP-like format.
The listing below shows how to load the trained MLP:

```
/*NN used for recognition*/
  lti::MLP annc;

//path to the NN file
  std::ifstream inNN("...\\TrainedNN.dat");

//stream handler for reading
    lti::lispStreamHandler lsh_c(inNN);

//read NN settings from file and close it
  annc.read(lsh_c);
  inNN.close();
```

At the end of this procedure, the MLP called *annc* has inherited all the "experience" of the previously trained matrix.
The next step consists in building an output classification vector and an input feature vector with the data to process:

```
//the vector that will contains the MLP answer
  lti::MLP::outputVector result;

//the vector containing the feature to classify
  lti::dvector feature_to_classify(3,NN_class_data);
```

where NN_class_data is an array of double containing the three RMS generated for the user's movement.
Note that the output vector is not a generic array, but it is an object of *outputVector* class; this structure is a special data type designed to give some information about the classification result of the network (e.g. the classification confidence).
In the last step, the MLP classify the provided dataset, filling the previously described outputVector:

```
//perform classification
  annc.classify(feature_to_classify,result);
```

Once the performed gesture has been identified, it can be displayed on the screen or employed to control an application.

Chapter 7

Steps in testing and final results

"Spock: Don't grieve, Admiral. It is logical. The needs of the many outweigh...
Kirk: ... the needs of the few.
Spock: ... or the one. I never took the Kobayashi Maru test. Until now. What do you think of my solution?
I have been, and always shall be your friend.
Live long... and prosper."

Star Trek II - The Wrath of Khan

Once all the units of Eracle have been developed, some tests have been executed, to estimate the system performance. The first paragraph of this chapter describes the procedure that has been adopted for all the trials.
Many tests have been carried out during the project development (we've performed about 100 different trials), however we would like to give an idea of how the project has evolved and which are the experimental results that have lead us to the achievement of a fully mobile device that correctly identifies at least five different gestures. The second section of this chapter provides some experimental results presented following this point of view.

7.1 Test procedure

First of all it is necessary that the user wears the acquisition glove (described in chapter 6, section 6.2) that will be connected to the devkit (described in chapter 5, section 5.1). The acquisition glove ensures repeatability during all the experiment. It means that we have to be sure that the electrodes are always placed nearly the same position, even if some time has elapsed between training and recognition stage. This feature of acquisition glove will be demonstrated in the next section.

Test stage is mainly divided in two different phases: training and classifying.

Training stage

This step is fully handled by EracleACQ, the executable file described in chapter 3, section 3.3.
During training stage, the user performs each movement several times to train the Neural Network classifier. Up to five gestures have been employed to test the application. Depending on the recognizer settings (see next section), every movement have been executed between 5 and 20 times.
The user can perform the training movements either standing or sitting.
Eracle has been tested with five different gestures:

- **close hand;**
- **wrist extension;**
- **wrist flexion;**
- **open hand;**
- **click.**

These movements have already been described in chapter 3, section 3.1.

Once the user has performed the requested repetitions of one movement, he rests his forearm since the muscular fatigue could invalidate the sampled acquired (see B). During this break, the computing core of Eracle processes the sampled data. As previously described in chapter 6, the whole processing chain of the training stage consists in:

- *parsing:* each input data file is splitted into three different sources;
- *FastICA:* that filters the sampled signals;
- *RMS:* that computes the Root Mean Square value for each source channel of each repetition;

Once this process has been repeated for all the gestures, the Neural Network is trained using the previously computed RMS values. The training time depends on the Neural Network settings; the classifier employed in the last set of tests (that is able to recognize up to five different gestures) needs between 10s and 15s for the training stage.
At the end of this stage EracleACQ generates a .dat file that stores the weights of the trained Neural Network.

Recognition stage

This step is fully handled by EracleREC, the executable file described in chapter 3, section 3.3.
In this stage the user performs just one movement (among those used for training)

and the device tries to recognize it.
To test the application, the users repeat each gesture alternately for ten times.

At the end of the ten repetitions of each gesture, the average success rate of the test is computed. Both in training and in recognition stage, the user should performs the gestures in a natural way, it means without "force" the movement. However, Eracle has demonstrated to be robust with respect to this feature. In fact, all the results provided in the next section have been achieved by executing the movement with different strength.

7.2 Results

During the test stage, we mainly focused on the recognizer's performance in order to identify the best settings for Neural Network and FastICA algorithm. It entails that almost all the test described in this chapter are referred to the same subject with these characteristics:

- Gender: *Male*
- Age: *24*
- Height: *177 cm*
- Weight: *68 kg*
- B.M.I: *22*

The last value is the Body Mass Index that briefly describes the physique of the user. B.M.I. between 18,5 and 25 identifies a medium-build man.

7.2.1 First set of tests: two gestures

In the first set of tests the user performs only two movements: close hand and wrist extension.
The neural network classifier has been set as follows:

- 3 input neurons, 2 output neurons;
- 6 neurons in the hidden layer;
- 2000 training epochs;
- learning rate: 0,1;
- learning algorithm: generalized Delta Rule (Backpropagation) .

The number of neurons in the hidden layer has been set according to the following thumb rule:

$$Hidden\,Neurons = Input\,Neurons \times Output\,Neurons \tag{7.1}$$

Each movement has been repeated 10 times during the training process. In this trial no additional preprocessing or postprocessing have been added to FastICA module, thus we employ the FastICA algorithm provided by LTIlib "as it is".
Matrix W has been kept constant for each gesture during all the training process.
The results of this test are shown in table 7.1.

Gesture	**Success/Tot**	**Errors/Tot**	**Test performance**
Close	8/10	2/10	60%
Wrist extension	4/10	6/10	

Table 7.1: Results of the first test; in FastICA algorithm matrix W has been kept constant

The next test has been carried out maintaining the settings of the previous one, the only difference is that matrix W has been computed for each movement repetition .
The results of this trial are shown in table 7.2.

Gesture	Success/Tot	Errors/Tot	Test performance
Close	7/10	3/10	70%
Wrist extension	7/10	3/10	

Table 7.2: Results of the first test, matrix W is computed for every repetition

Looking at these two results, it is clear that the second trial is better than the first one. This result confirms what we have already discussed in chapter 6, section 6.3: computing the unmixing matrix for each single movement repetitions makes the system more robust.

7.2.2 Improving the classifier

However, these two results are not satisfactory, since the success rate is too low.
The Neural Network employed for recognizing these two gestures seems oversized. Six neurons and 2000 training epochs look like too much for a classifier that simply distinguishes between two classes of data. In the second set of tests we simplify the Multi Layer Perceptron as follows:

- 3 input neurons, 2 output neurons;
- 2 neurons in the hidden layer;
- 100 training epochs;
- learning rate: 0,1;
- learning algorithm: generalized Delta Rule (Backpropagation) .

We increase the number of movement repetitions employed in training set from 10 to 20 (for each gesture). As in the previous set of tests, we haven't added any additional feature to the FastICA algorithm provided by LTIlib. Moreover, matrix W has been kept constant (for the same class of movements).
Table 7.3 summarizes the results of this trial; the two tests have been performed in the same day, without taking off the acquisition glove:

Gesture	Success/Tot	Errors/Tot	Test performance
Close	10/10	0/10	95%
Wrist extension	9/10	1/10	

Close	7/10	3/10	75%
Wrist extension	8/10	2/10	

Table 7.3: Results of the second test, matrix W is kept constant

We have repeated the experiment computing the W matrix for every movement repetition. The Neural Network is the same of the previous test. Table 7.4 shows the results obtained in two experiments performed without taking off the acquisition glove:

Gesture	**Success/Tot**	**Errors/Tot**	**Test performance**
Close	8/10	2/10	85%
Wrist extension	9/10	1/10	
Close	7/10	2/10	80%
Wrist extension	8/10	2/10	

Table 7.4: Results of the second test, matrix W is computed for every repetition

By looking at these results, it is not clear which one of the two solutions performs better.
After a bit of time we have repeated the experiment, table 7.5 shows the results obtained by keeping the unmixing matrix constant (for the same class of gestures):

Gesture	**Success/Tot**	**Errors/Tot**	**Test performance**
Close	5/10	5/10	55%
Wrist extension	6/10	4/10	

Table 7.5: Repetition of the second test, matrix W is kept constant

Instead, table 7.6 reports the results obtained by computing the unmixing matrix W for every gesture repetition:

Gesture	**Success/Tot**	**Errors/Tot**	**Test performance**
Close	10/10	0/10	75%
Wrist extension	5/10	5/10	

Table 7.6: Repetition of the second test, matrix W is computed for every gesture repetition

By looking at these two last results it is clear that keeping the unmixing matrix constant brings to a lack of performance of the recognizer. This result definitively confirms the hypothesis formulated in chapter 6, section 6.3: computing the unmixing matrix for each single movement repetitions makes the system more robust.

7.2.3 From two to four gestures

By working with only two movements we have found that the unmixing matrix W must be kept constant for all the repetitions of the same gesture during the training stage. However, a gesture recognition device that distinguishes only between two gestures is not very useful.
The next goal is to raise the number of recognized gestures from two to at least four.
Table 7.7 shows the results obtained with the same architecture employed in the previous test working on three gestures (close hand, wrist extension and wrist flexion). There are only two differences between this solution and the previous one:

- the number of hidden neurons has been increased to 9 (following the thumb rule quoted in equation 7.1);
- the number of training epochs has been increased to 500;

Gesture	**Success/Tot**	**Errors/Tot**	**Test performance**
Close	5/10	5/10	53%
Wrist extension	8/10	2/10	
Wrist flexion	3/10	7/10	

Table 7.7: Third test: the Neural Network tries to classify three different gestures

Performance gets even worse if we use the same recognizer on four different gestures (adding open hand movement), as shown in table 7.8:

Gesture	**Success/Tot**	**Errors/Tot**	**Test performance**
Close	3/10	7/10	38%
Wrist extension	0/10	10/10	
Wrist flexion	7/10	3/10	
Open hand	5/10	5/10	

Table 7.8: Third test: the Neural Network tries to classify four different gestures

Increasing or decreasing the number of neurons or the training epochs haven't improved the performance, so we have introduced the features discussed in chapter 6, section 6.3 regarding the FastICA module. These additional features mainly consists in preprocessing and postprocessing operations that have been suggested by the Matlab implementation of FastICA algorithm proposed by Hyvärinen ([33]) and developed by the Laboratory of Computer and Information Science at the Helsinki University of Technology ([10]).
Moreover - as stated in chapter 4, section 4.3.2 - FastICA algorithm requires some preprocessing in order to be correctly applied.
The introduction of these preprocessing and postprocessing stages have led to a sensible improvement of Eracle's performance.

The first interesting test has been carried out using a Neural Network with the following settings:

- 3 input neurons, 4 output neurons;
- 12 neurons in the hidden layer;
- 500 training epochs;
- learning rate: 0,1;
- learning algorithm: generalized Delta Rule (Backpropagation) .

We have trained the Neural Network with only five repetitions of each gesture. Table 7.9 summarizes the test results:

Gesture	**Success/Tot**	**Errors/Tot**	**Test performance**
Close	10/10	0/10	63%
Wrist extension	0/10	10/10	
Wrist flexion	50/10	5/10	
Open hand	10/10	0/10	

Table 7.9: Eracle's performance on four gestures after FastICA modifications

Despite the average performance (that is still too low), it is important to analyze the output of the recognizer:

- *close hand* and *open hand* have been always correctly identified;
- *wrist extension* has always been confused with the *open hand* movement;
- *wrist flexion* has sometimes been confused with *close hand* movement.

These observations perfectly fit with the hypothesis discussed in the previous chapter in section 6.3, thus there are some patterns are more likely to be confused than others. Looking at table 7.10 it is clear that the recognizer can distinguish between *Wrist extension* and *open hand* only by looking at the first input channel, that is

higher in the first gesture. It is also easy to make a mistake between *close hand* and *wrist flexion* since the only difference between these two gestures is the value of the third channel, that is higher in the first movement.

Gesture	Channel 1	Channel 2	Channel 3
Close hand	9,846	9,053	8,763
	9,833	7,675	7,408
	8,303	8,224	7,087
	9,589	6,789	4,843
	9,685	6,978	6,1623
Wrist extension	33,274	5,188	16,283
	35,861	5,415	8,717
	29,897	4,789	7,049
	27,923	4,473	14,026
	29,053	4,090	13,411
Wrist flexion	15,871	13,528	4,513
	14,675	11,895	3,789
	18,899	19,002	3,123
	13,298	12,213	3,852
	18,911	19,050	3,369
Open hand	15,125	6,750	16,249
	17,146	6,926	10,424
	15,765	7,321	13,237
	16,765	7,543	16,145
	15,072	7,369	15,992

Table 7.10: An excerpt of RMS values employed for training and recognition

The described classifier (with only two neurons in the output layer) can easily distinguish between *wrist extension* and *close hand* movements, as outlined by table 7.11:

Gesture	Success/Tot	Errors/Tot	Test performance
Close	10/10	0/10	100%
Wrist extension	10/10	0/10	

Table 7.11: Eracle's performance in recognizing two different gestures

The following step consists in adding a new movement to the set of gesture that will be classified by Eracle. To distinguish among three different movements it is

necessary to make the network more "sensitive" to the differences described above. To achieve this result the training epochs have been increased and the learning rate has been decreased. This last choice will lead to a lack in performance during the training stage, but it avoids that the training algorithm converges to a local minimum.
We have selected *open hand* as additional gesture. The Neural Network has been set as follows:

- 3 input neurons, 3 output neurons;
- 12 neurons in the hidden layer;
- 1000 training epochs;
- learning rate: 0,01;
- learning algorithm: generalized Delta Rule (Backpropagation) .

We employ 10 repetitions of each gesture during the training stage.
The test results are summarized in table 7.12:

Gesture	**Success/Tot**	**Errors/Tot**	**Test performance**
Close	10/10	0/10	93%
Wrist extension	9/10	1/10	
Open hand	9/10	1/10	

Table 7.12: Eracle's performance on three different movements

In the last step of this test stage, we have also added the *wrist flexion* gesture to the set of movements that will be classified by Eracle. There's practically no differences between this classifier and the previous one except the number of output neurons (that has been increased to four) and the number of training epochs (that has been increased to 1000).
Table 7.13 shows the test results:

Gesture	**Success/Tot**	**Errors/Tot**	**Test performance**
Close	10/10	0/10	85%
Wrist extension	9/10	1/10	
Wrist flexion	10/10	0/10	
Open hand	5/10	5/10	

Table 7.13: Eracle's performance on four gestures

To improve the recognizer performance we have increased the training epochs to 1500. Also in this trial, the Neural Network has been trained with 10 repetitions

of each gesture.
Table 7.14 shows the results of two different tests; it is important to point out that they have been performed in different days.

Gesture	Success/Tot	Errors/Tot	Test performance
Close	10/10	0/10	98%
Wrist extension	9/10	1/10	
Wrist flexion	10/10	0/10	
Open hand	10/10	0/10	
Close	9/10	1/10	88%
Wrist extension	10/10	0/10	
Wrist flexion	8/10	2/10	
Open hand	8/10	2/10	

Table 7.14: Eracle's performance with four gestures. The two tests have been executed in different days

This last two trials show that Eracle is able to distinguish among four gestures with a global performance of 93%.

7.2.4 Tests with different subject

The trials presented in this paragraph have been performed by a subject with these characteristics:

- Gender: *Female*
- Age: *22*
- Height: *156 cm*
- Weight: *41 kg*
- B.M.I: *17*

This subject has a really different physique from the one described at the beginning of these section.
The Neural Network settings are the same of the last test, thus:

- 3 input neurons, 4 output neurons;
- 12 neurons in the hidden layer;
- 1500 training epochs;
- learning rate: 0,01;
- learning algorithm: generalized Delta Rule (Backpropagation) .

Concerning the first test, the Neural Network has been trained with the example set of the first subject (10 repetitions for each movement). Since the physique of the two subjects is very different, we haven't obtained very good results, as shown in table 7.15:

Gesture	Success/Tot	Errors/Tot	Test performance
Close	10/10	0/10	55%
Wrist extension	10/10	0/10	
Wrist flexion	2/10	8/10	
Open hand	0/10	10/10	

Table 7.15: Eracle's performance with four gestures: the classifier has not been trained with the data of the current user

Once the second subject has trained the Neural Network with its own data, we have performed another test with the following results:

Gesture	Success/Tot	Errors/Tot	Test performance
Close	10/10	0/10	85%
Wrist extension	9/10	1/10	
Wrist flexion	9/10	1/10	
Open hand	6/10	4/10	

Table 7.16: Eracle's performance with four gestures: the neural network has been trained by the current user

In the last test we have increased the number of training epochs from 1500 to 2000, table 7.17 shows the trial results:

Gesture	Success/Tot	Errors/Tot	Test performance
Close	10/10	0/10	93%
Wrist extension	10/10	0/10	
Wrist flexion	10/10	0/10	
Open hand	7/10	3/10	

Table 7.17: Eracle's performance with four gestures: the number of epochs has been increased

These last results outline that Eracle is able to distinguish among four different gestures with a good success rate (about 90%). This result is really meaningful, as

the second subject has never employed a gesture recognition system.
This trial also points out the relevance of employing a correct set of data in the training stage.

7.2.5 Last set of tests: five gestures

In this last paragraph, Eracle has been tested in recognizing five different movements.
The fifth gesture is called "click", as it could be employed as the left click of a mouse (as described in chapter 3, section 3.1. These tests have been performed by the first user described at the beginning of this section.
For this set of tests, the Neural Network has been set as follows:

- 3 input neurons, 4 output neurons;
- 12 neurons in the hidden layer;
- 2000 training epochs;
- learning rate: 0,01;
- learning algorithm: generalized Delta Rule (Backpropagation) .

Every movement has been performed ten times during the training stage.
Table 7.18 shows the result of two trials that have been performed in different times.

Gesture	Success/Tot	Errors/Tot	Test performance
Close	10/10	0/10	95%
Wrist extension	10/10	0/10	
Wrist flexion	9/10	1/10	
Open hand	9/10	1/10	
Click	7/10	3/10	
Close	9/10	1/10	88%
Wrist extension	9/10	1/10	
Wrist flexion	9/10	1/10	
Open hand	8/10	2/10	
Click	7/10	3/10	

Table 7.18: Eracle's performance in classifying five gestures

Eracle has achieved a global performance of about 90% in recognizing five different gestures. Note that the classifier is approximately the same employed to recognize four gestures performed by the first subject.
This leads us to the consideration that the device should be able to recognize more than five gestures with a good performance rate (see chapter 8, section 8.1).

Chapter 8

Conclusions and future developments

Chekov: Course heading, Captain?
Kirk: Second star to the right. And straight on 'til morning.
Captain's log. Stardate 9529.1. This is the final cruise of the starship Enterprise under my command. This ship and her history will shortly become the care of another crew. To them and to their posterity we will commit our future. They'll continue the voyages we have began and they will journey to all the undiscovered countries, boldly go where no man, where no one... has gone before.

Star Trek VI - The Undiscovered Country

In this work we have described Eracle, which is a gesture recognition system based on EMG signals. Moreover, this device is fully implemented with mobile technologies, thus the user wears the sampling unit of the device as a glove, while the computing core can fit into a pocket.
Eracle is designed to be employed in Virtual Reality simulations like video games or Augmented Reality applications. Due to its little size and weight, this system could also be used by everyone in daily life Human Computer Interaction.
Providing some improvements, Eracle could also be applied in an industrial context to control a robotic arm.
This system is also suitable for home automation, to control domestic appliances like television or air-conditioner simply by moving a hand.
Finally, this device could be employed in hand prosthesis control field, although it would be necessary adding some features like the detection of different grasps (see chapter 2, section 2.1.2)

Eracle has achieved good results in test stage, since it is able to recognize five or four gesture with an average performance of about 90%. It is interesting to point out that the classifier has been trained with very few examples; as described

in the previous chapter, only ten repetitions of each movement are necessary to distinguish among five different gestures.
We think that the global performance will be improved if the user employs the device for enough time. Think about using a mouse, when you move it for the first time it is difficult that the pointer moves exactly where you want; however, after some trial, the device become familiar and you interact with the PC without any problem. This simple consideration holds also for Eracle: the more you employ it, the best it performs, as the user fits his movement to obtain the best performance.

8.1 Future developments

The prototype of Eracle performs well in recognizing up to five different gestures, but there are several features that can be improved in future works.

Computational speed

This prototype of Eracle has been developed focusing on recognition accuracy.
All the units of Eracle's computing core have been designed to be as independent as possible, it means that every module reads some input data from files and stores the output results in other files. This choice is mainly dictated by debugging purposes, as we can easily monitor every step along the processing chain. The main drawback of this solution is the loss in computational speed, mainly due to the huge amount of I/O operations performed by each module of the computing core. By removing some I/O operations, it is possible to improve the recognizer speed; we estimate that the computational time could be reduced to half of the current one. Thus, introducing some optimization and removing some I/O operations we hypothesize that it is possible to sample and recognize each movement in about four seconds. Moreover, we think that Eracle could correctly performs gesture recognition with less than 1010 samples for each input channel, so we will reduce the sampling time in order to improve the global speed.
As discussed in the previous section, this system could be employed to control a robotic arm in industrial context. Computational speed is a key feature in this field, as Eracle should recognize gestures in real time in order to be employed on an industrial production line.

Classifier adaptability

Some EMG manuals ([52]) and some experiments outline that physiological elements like sweating, skin temperature or muscle fatigue can worsen the recognizer's performance. Changes in some of these biometric values can be easily detected with sensors enclosed in the acquisition glove. This input data could be employed by the computing core to adjust the settings of the classifier in order to achieve always a good performance.
For example, some corrective formulas are already employed in medical examination as described in [52].
Another possible solution could be to train the Neural Network with two different datasets. The first dataset will contain the data sampled from "rested" muscles, while the other one will provide values sampled from the "stressed" muscles.

More gestures

Identifying up to five gestures is a good result for an EMG-based recognizer. Eracle obtains an average performance of about 90% providing only ten repetitions of each gesture as training set. This result suggests that Eracle could recognize more than

five gestures with a good performance. By providing more training examples, we think that this device could be able to handle up to seven or eight different gestures.

Acquisition glove

The acquisition glove employed in this project (described in chapter 6, section 6.2) is a prototype. A future version of this device could be realized with elastic material like Lycra; moreover the wires and the EMG board could be hided inside the glove. To sample the EMG signals we use commercially available electrodes employed for electro stimulators appliances. These electrodes are not designed for prolonged use and their surface degrades quickly. This leads to an increase in signal's noise and in a lack in recognizer's performance.
Signal's quality could be increased by employing professional equipment like *Trigno Wireless System* by Delsys ([7]). This device provides up to 16 EMG channels and triaxial accelerometers to correctly identify the user movement. Moreover, this device is really small (37mm x 26mm x 15mm) and provide at least 8 hours of battery operations.
Due to its reduced size and battery life, this device could be easily integrated in Eracle's acquisition glove.

Wavelet transform

The accuracy performance of Eracle in recognizing up to five different gestures is good; however - ad described both in chapter 6, section 6.3 and in chapter 7, section 7.2 - it is easy to confuse some of the movements, since in some cases the difference is due to just a single input channel. So, it would be interesting to add a new unit in the computing core of Eracle that helps the recognizer in identifying the features of the input signals. Both FastICA and Wavelet could be employed in the filtering stage. Wavelet has been proposed by Mallat in [39] and has been widely used for feature extraction in signal processing.
Moreover, LTIlib provides a basic implementation of Wavelet employed in image processing.

Wi-fi connection

Currently, the output of Eracle has been displayed on a screen thanks to the VGA output of the devkit (described in chapter 5, section 5.1). However, this device could be connected to a wide range of appliances as the Tegra devkit provides both USB and Ethernet output.
Moreover, an interesting future development consists in connecting Eracle to other devices using wireless Wi-Fi technology like ZigBee. This feature will avoid wired connection to an external device, making Eracle more wearable and easy-to-use.

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Appendix A

Code listing

A.1 Eracle Serial Port Manager

```
/*****************************************************
*EracleSerialPortManager.cpp:
Read data generated by sEMG board for NUM_ACQ times.
Data are stored in \\Storage Card\\DatiNUM_ACQ.
Every burst fill a CHAR buffer of 15000 elements.
*****************************************************/

#include "stdafx.h"
#include "Eracle.h"
#include <iostream>
#include <sstream>
#include "s2ws.h"



#define MAX_LOADSTRING 100

//number of training movements
#define NUM_ACQ 10

//number of samples
#define DIM_CHANNEL 1010



using namespace std;
```

```
void EracleSerialPortManager(){

  HANDLE hSer; /*FTDI port handler*/
  HANDLE hFile; /*data file handler*/
  INT rc;
  BYTE szText[10]={0x41,0x42,0x43,0x44,0x45};
  CHAR buffer [15000]; /*read buffer of FTDI port*/
  DWORD bytesRead;

  int indice =1;  //while loop index
  ostringstream oss; //service stream for itoa conversion


  while(indice <= NUM_ACQ){

    /*this loop run for NUM_ACQ cycles,
    at every iteration one different data
    file is created and filled with sEMG board data*/

    /*itoa conversion of loop index,
    to mark the data file*/
    oss<<indice;
    string index = oss.str();

    /* create a file which emulate the FTDI / serial port.
    File must be named $device\COM10 */

    hSer=CreateFile(TEXT("$device\\COM10"),
            GENERIC_READ|GENERIC_WRITE,0,
            NULL,OPEN_EXISTING,0,NULL);

    if(hSer==INVALID_HANDLE_VALUE){
      MessageBox(NULL,TEXT ("Port is not opened"),
                 TEXT("EracleSerialPortManager"),MB_OK);
      exit(0);
    }


    /* serial port settings*/

    DCB dcb;
    dcb.DCBlength=sizeof(dcb);
    GetCommState(hSer,&dcb);
    dcb.BaudRate=57600;
    if(SetCommState(hSer,&dcb)) {
```

```
  MessageBox(NULL,
  TEXT ("Port is opened with baud rate 57600
  - Ready to sEMG acquisition !!!
    \nPRESS ENTER TO BEGIN ACQUISITION"),
  TEXT("EracleSerialPortManager"),MB_OK);
}

PurgeComm(hSer,PURGE_TXABORT | PURGE_RXABORT |
               PURGE_TXCLEAR | PURGE_RXCLEAR);

/* check if you can read from FTDI port...
...if ok, read and put data in buffer*/
if(rc =ReadFile(hSer,buffer,sizeof(buffer),&bytesRead ,0))
  MessageBox(NULL,TEXT("END OF ACQUISITION"),
             TEXT("EracleSerialPortManager"),MB_OK);


/*definition of data file name and path*/
string pre = "\\Storage Card\\Eracle_Acquisizioni\\DATI";
string suff = ".txt";
string path = pre+index+suff;


std::wstring stemp = s2ws(path);
LPCWSTR result = stemp.c_str();


hFile = CreateFile(result,
  (GENERIC_READ | GENERIC_WRITE),
  0, NULL, CREATE_ALWAYS, FILE_ATTRIBUTE_NORMAL, NULL);


if(!(WriteFile(hFile,buffer, sizeof(buffer),&bytesRead, 0))){
  MessageBox(NULL,TEXT("Error in file writing"),
             TEXT("EracleSerialPortManager"),MB_OK);
  exit(0);
}

/*close file handlers*/
CloseHandle(hFile);

CloseHandle(hSer);

indice++; //while loop variable increase
```

```
    //service stream flush
    oss.str("");
    oss.clear();
  }


  MessageBox(NULL,TEXT("End of acquisition procedure"),
             TEXT("EracleSerialPortManager"),MB_OK);


return;
}
```

A.2 Eracle Parser

```
/*************************************************************
EracleParser.cpp:
*
Read (one by one) the files generated by
EracleSerialPortManager and split them into three
different files: one file for each channel.
Input files are limited to DIM_CHANNEL samples each.
Every input files is also cleaned from spurious data at
the beginning and at the end of the stream.

Input files are stored in
\\Storage Card\\Eracle_Acquisizioni
Output files (three for each input file) are stored in
\\Storage Card\\Eracle_Parser in a subfolder
named after the acquisition step of acquisition.
*************************************************************/

#include "stdafx.h"
#include "Eracle.h"
#include <fstream>
#include <algorithm>
#include <sstream>

#include "s2ws.h"

#define MAX_LOADSTRING 100

//resture repetitions
#define NUM_ACQ 10

//number of samples
#define DIM_CHANNEL 1010


using namespace std;



void EracleParser (){

  int indiceParser=1;

  ostringstream ossParser;
```

```
  MessageBox(NULL, TEXT("Begin of parsing"),
             TEXT("EracleParser"), MB_OK);


  while(indiceParser<=NUM_ACQ){
    int posD=0;

    fstream input_data; //input stream to get data

    //the three resulting files, one per channel
    fstream Channel_1, Channel_2, Channel_3;

    /*the string that will contain all
    the emg board's output (file DATA.txt)*/
    string tot = "";

    /*strings for parser input*/
    string parserInputPrefix =
      "\\Storage Card\\Eracle_Acquisizioni\\DATI";

    string parserSuffix = ".txt";

    ossParser<<indiceParser;

    //string with number of file that will be parsed
    string parserNumFile = ossParser.str();

    string parserInputPath =
    parserInputPrefix+parserNumFile+parserSuffix;


    std::wstring stemp = s2ws(parserInputPath);

    //parser input result is the path to the file to be open
    LPCWSTR parserInputResult = stemp.c_str();


/*strings for parser output*/

    string parserOutputPrefix =
    "\\Storage Card\\Eracle_Parser\\Acq";


    /*create one directory for
```

```
each acquisition in folder Eracle_Parser*/

string parserOutFolder =
parserOutputPrefix+parserNumFile;

std::wstring stemp1 = s2ws(parserOutFolder);
LPCWSTR parserFolderResult = stemp1.c_str();

CreateDirectory(parserFolderResult,NULL);


string parserFileOutput1 = "\\Channel_1.txt";
string parserFileOutput2 = "\\Channel_2.txt";
string parserFileOutput3 = "\\Channel_3.txt";

string parserPathOutput1 = parserOutFolder+
                           parserFileOutput1;
string parserPathOutput2 = parserOutFolder+
                           parserFileOutput2;
string parserPathOutput3 = parserOutFolder+
                           parserFileOutput3;

std::wstring stemp_uno = s2ws(parserPathOutput1);
std::wstring stemp_due = s2ws(parserPathOutput2);
std::wstring stemp_tre = s2ws(parserPathOutput3);

LPCWSTR parserOutPath1Result = stemp_uno.c_str();
LPCWSTR parserOutPath2Result = stemp_due.c_str();
LPCWSTR parserOutPath3Result = stemp_tre.c_str();


//open stream to read data file
input_data.open(parserInputResult, fstream::in);



//open stream to the three output files
Channel_1.open(parserOutPath1Result,fstream::out);
Channel_2.open(parserOutPath2Result,fstream::out);
Channel_3.open(parserOutPath3Result,fstream::out);


/*check for file opening error*/
if ((input_data.fail())||(Channel_1.fail())||
  (Channel_2.fail())||(input_data.fail())||
```

```
    (Channel_3.fail())){
    MessageBox(NULL,TEXT ("Error in opening files"),
               TEXT("EracleParser"),MB_OK);
    exit(0);
  }


  /*read all the data in input stream and
  store them in string tot*/
  while(input_data.good()){
    getline(input_data,tot);
  }




/*****************************************
BEGIN OF PARSING ************************
*****************************************/



/*(((1))) replace newline and carriage return with spaces*/

  replace(tot.begin(), tot.end(), '\r', ' ');
  replace(tot.begin(), tot.end(), '\n', ' ');



/*(((2))) find and erase spurious
input vector at the begin of data*/

  posD=tot.find("D"); //find the position of the first D

  if(posD!=0){ //if file doesn't begin with D...

    tot.erase(0,posD); //... erase alla charachters before D
  }



/*(((3))) delete the last input vector,
to prevent spurious data at the end of stream*/

  size_t ultimo;
```

```
  size_t fine;

  //get the position of last D...
  ultimo = tot.rfind("D");

  //... and the position of the termination char
  fine = tot.rfind("\0");

  //delete last row, but don't erase "\0" charachter
  tot.erase(ultimo, fine-1);



/*((4))) count the number of D
      --> this is also the number of rows
      --> this is also the number of "good" data acquired*/

  //numbers of "clean" data acquired
  int conteggio = count(tot.begin(),tot.end(),'D');

  if(conteggio<DIM_CHANNEL){
    MessageBox(NULL, TEXT("Pochi campioni"),
    TEXT("EracleParser"), MB_OK);
    exit(0);
  }



/*(((5))) split string tot in three files,
each column to a file, each data separated
by a blank spaces (included the last one)*/

  size_t begin,end;

  //get the indeces of the first number in first row
  begin = tot.find("D");
  end = tot.find(" ");

  int index;

  int row_count=0;

  //run until 1010 lines have been parsed
  while(row_count < DIM_CHANNEL){
```

```
/*for the first number indeces
have already been acquired*/
  if(row_count>0){
    begin = tot.find("D",end);
    end = tot.find(" ",begin+1);
  }


  //first number of the triple --> to file Channel_1
  for(index = static_cast<int>(begin)+2;
      index<static_cast<int>(end);index++){
    Channel_1<<tot[index];
  }
  Channel_1<<" ";

  //adjust indeces
  begin = tot.find(" ",end);
  end = tot.find(" ",begin+1);

  //second number of the triple --> to file Channel_2
  for(index = static_cast<int>(begin)+1;
      index<static_cast<int>(end);index++){
    Channel_2<<tot[index];
  }
  Channel_2<<" ";

  //adjust indeces
  begin = tot.find(" ",end);
  end = tot.find(" ",begin+1);

  //last number of the triple --> to file Channel_3
  for(index = static_cast<int>(begin)+1;
      index<static_cast<int>(end);index++){
    Channel_3<<tot[index];
  }
  Channel_3<<" ";


  row_count++;
}


/*close all streams*/
Channel_1.close();
Channel_2.close();
```

```
    Channel_3.close();
    input_data.close();

    //parsingCheck(conteggio);

    //clear the itoa buffer
    ossParser.str("");
    ossParser.clear();

    indiceParser++; //loop variable++

  }

  MessageBox(NULL,TEXT ("End of Parsing"),
             TEXT("eracleParser"),MB_OK);


return;

}
```

A.3 Eracle FastICA

```
/*******************************************************
EracleFastICA.cpp:
*
Open the files previously generated by the parser and:
- compute and subtract the average value of
  each channel (remmean);
- compute the unmixing matrix;
- apply FastICA algorithm;
- Add the mean back to the data.
In the output result of ICA are corrected with
a mean calculation inspired from
MATLAB implementation of FastICA.

The output vectors are stored in three separated files
in Eracle_FastICA: three files for
each sampling (one per channel).
*******************************************************/

#include "stdafx.h"
#include "Eracle.h"
#include <iostream>
#include <string>
#include <fstream>
#include <sstream>

#include "ltiVector.h"
#include "ltiMatrix.h"
#include "ltiFastICA.h"
#include "s2ws.h"

using namespace std;


#define MAX_LOADSTRING 100

//number of gesture repetitions
#define NUM_ACQ 10

//number of samples
#define DIM_CHANNEL 1010


void EracleFastICA(){
```

```
MessageBox(NULL, TEXT("Begin of FastICA"),
           TEXT("EracleFastICA"), MB_OK);


//variables for loop control and itoa conversion
int indiceICA = 1;
ostringstream ossICA;

while(indiceICA<=NUM_ACQ){

  //stream for summary operations
  fstream fastica_stream;

  /*input files; one for each channel,
  these files are produced
  by EracleParser() function*/
  FILE * Mazinga1;
  FILE * Mazinga2;
  FILE * Mazinga3;


  //FastICA path string input building
  string ICAInputfolderPrefix =
    "\\Storage Card\\Eracle_Parser\\Acq";

  ossICA<<indiceICA;
  string ICANumFile = ossICA.str();

  string ICAinput1 = "\\Channel_1.txt";
  string ICAinput2 = "\\Channel_2.txt";
  string ICAinput3 = "\\Channel_3.txt";

  string ICAInputfile1Path = ICAInputfolderPrefix +
                             ICANumFile + ICAinput1;
  string ICAInputfile2Path = ICAInputfolderPrefix +
                             ICANumFile + ICAinput2;
  string ICAInputfile3Path = ICAInputfolderPrefix +
                             ICANumFile + ICAinput3;


  /*it is not necessary to convert string to wstring,
  as fopen uses const char * to open file.
  String can be converted to const
```

```
char * using data() method*/

//output folder creation
string ICAOutputfolderPrefix =
  "\\Storage Card\\Eracle_FastICA\\Acq";

string ICAOutputFolder = ICAOutputfolderPrefix
                         + ICANumFile;

std::wstring ICAtemp0 = s2ws(ICAOutputFolder);
LPCWSTR ICAFolderResult = ICAtemp0.c_str();

CreateDirectory(ICAFolderResult,NULL);


//summary filestream string path
string ICAOutputSuffix = "\\FastICA.txt";

string ICAOutputSummary = ICAOutputFolder
                          + ICAOutputSuffix;

std::wstring ICAtemp = s2ws(ICAOutputSummary);
LPCWSTR ICASummaryResult = ICAtemp.c_str();



//Perform file and stream opening and check for errors

//open summary filestream
fastica_stream.open(ICASummaryResult, fstream::out);

/*check for stream opening error*/
if (fastica_stream.fail()){
  MessageBox(NULL,TEXT ("Error in opening filestream"),
             TEXT("EracleFastICA"),MB_OK);
  PostQuitMessage(0);
}


Mazinga1=fopen (ICAInputfile1Path.data(),"r");
Mazinga2=fopen (ICAInputfile2Path.data(),"r");
Mazinga3=fopen (ICAInputfile3Path.data(),"r");

if ((Mazinga1==NULL)||
  (Mazinga2==NULL)||
```

```
  (Mazinga3==NULL)) {/*check for files opening error*/
  MessageBox(NULL,TEXT ("Error in opening input files"),
             TEXT("EracleFastICA"),MB_OK);
  exit(0);
}


/*data array declarations - one per channel
 - and the "global" array tot*/
double ch1_data[DIM_CHANNEL];
double ch2_data[DIM_CHANNEL];
double ch3_data[DIM_CHANNEL];
double tot[DIM_CHANNEL*3];


//copy data from files to vectors
for(int k=0;k<DIM_CHANNEL;k++){
  fscanf(Mazinga1, "%lf", &ch1_data[k]);
  fscanf(Mazinga2, "%lf", &ch2_data[k]);
  fscanf(Mazinga3, "%lf", &ch3_data[k]);
}



/*check equal and fixed number of data acquired,
exit if different*/
if((sizeof(ch1_data)/sizeof(double)!=DIM_CHANNEL)||
  (sizeof(ch2_data)/sizeof(double)!=DIM_CHANNEL)||
  (sizeof(ch3_data)/sizeof(double)!=DIM_CHANNEL)){

  MessageBox(NULL,TEXT ("Array size error"),
             TEXT("EracleFastICA"),MB_OK);
  exit(0);

}


//fill the tot vector
int i;

for(i=0;i<DIM_CHANNEL;i++){
  tot[i]= ch1_data[i];
}
```

```
    for(i=DIM_CHANNEL;i<DIM_CHANNEL*2;i++){
      tot[i]=ch2_data[i-DIM_CHANNEL];
    }



    for(i=DIM_CHANNEL*2;i<DIM_CHANNEL*3;i++){
      tot[i]=ch3_data[i-DIM_CHANNEL*2];
    }



    /*matrix constructor: 3 rows (one per source)
    and DIM_CHANNEL columns*/
    lti::matrix<double> source(3,DIM_CHANNEL,tot),W,clean;


    //for fastICA rows and cols must be transposed:
    /*after transpose
    each ROW is an acquisition(input vector),
    so it contains one sample for each source
    each COL is the set of data acquired by a
    single channel
        CH1 CH2 CH3
      iV1  |   |   |
      iV2  |   |   |
       .   |   |   |       -->>> this is sourceT!!!
       .   |   |   |
       .   |   |   |
    */
    lti::matrix<double> sourceT;
    sourceT.transpose(source);


//+++++++++++++++++++++++++++++++++++++++++++++++++++++++
//*REMMEAN:
//compute the mean of each channel (column) and subtract
//it from the data
//before passing them to fastica*/

    double mean[3];
    double temporale=0;

    for(int j=0;j<3;j++){
```

```
      for(int i=0; i<DIM_CHANNEL; i++){
        temporale = temporale+sourceT.at(i,j);
      }

      mean[j]=temporale/DIM_CHANNEL;

    temporale = 0;
    }


    lti::matrix<double> media(1,3,mean);


    const double init =1;
    lti::matrix<double> ones(DIM_CHANNEL,1,init);

    lti::matrix<double> matmedia;

    matmedia.multiply(ones,media);

    sourceT.subtract(matmedia);


//++++++++++++++++++++++++++++++++++++++++++++++++++


      lti::fastICA<double> pippo;
      lti::matrix <double> constTransfMatrix;

      pippo.apply(sourceT,clean);

      pippo.getTransformMatrix(constTransfMatrix);


      lti::vector<double> vec;
      pippo.getOffsetVector(vec);

    /**********************************************
    mean correction of FastICA output
    (inspired by MATLAB FastICA package)

    uscita = W * unmixedsig + (W * mixedmean)
            * ones (1,NumOfSampl);

    **********************************************/
```

```
lti::matrix<double> primoMembro;

/*primoMembro = W*unmixedsig
unmixedsig is FastICA output,
it must be transposed in cleanT to be multiplied*/
lti::matrix<double> cleanT;
cleanT.transpose(clean);
primoMembro.multiply(constTransfMatrix,cleanT);



/*v=W*mixedmean:
before multiply b v contains the mean of
the input data (mixedmean);
after multilply b is the result of the operation*/
lti::vector<double> v;
pippo.getOffsetVector(v);
constTransfMatrix.multiply(v);



/*v must be transposed to compute
the last multiply
(but there's no tranpose method
for vectors in LTILIB)*/
double appoggio[3];
for(int h=0;h<3;h++){ //"homemade" transpose
  appoggio[h]=v.at(h);
}


/*as in LTILIB doesn't exists a column vector,
a 3x1 matrix is used
appoggioMatrice = (W * mixedmean)*/
lti::matrix<double> appoggioMatrice (3,1,appoggio);


/*a matrix full of ones, in MATLAB it would be:
unii=ones(1,DIM_CHANNEL)*/
const double inival =1;
```

```
    lti::matrix<double> unii(1,DIM_CHANNEL,inival);


    //secondoMembro = appoggioMatrice*unii
    lti::matrix<double> secondoMembro;
    secondoMembro.multiply(appoggioMatrice,unii);


    //uscita = primoMembro + secondoMembro
    lti::matrix<double> uscita,uscitaT;
    uscita = primoMembro+secondoMembro;


    //transposing matrix uscita, just for reading purpose
    uscitaT.transpose(uscita);


  /*********************************************************/


    //FastICA output file path string building
    string IcaOutput1 = "\\Clean1_ICA.txt";
    string IcaOutput2 = "\\Clean2_ICA.txt";
    string IcaOutput3 = "\\Clean3_ICA.txt";

    string ICAInputFile1Path = ICAOutputFolder
                               + IcaOutput1;
    string ICAInputFile2Path = ICAOutputFolder
                               + IcaOutput2;
    string ICAInputFile3Path = ICAOutputFolder
                               + IcaOutput3;

    std::wstring ICAtemp1 = s2ws(ICAInputFile1Path);
    std::wstring ICAtemp2 = s2ws(ICAInputFile2Path);
    std::wstring ICAtemp3 = s2ws(ICAInputFile3Path);
    LPCWSTR ICAInputFile1Result = ICAtemp1.c_str();
    LPCWSTR ICAInputFile2Result = ICAtemp2.c_str();
    LPCWSTR ICAInputFile3Result = ICAtemp3.c_str();


    //files for EracleFastICA output
    fstream clean1,clean2,clean3;
```

```
    clean1.open(ICAInputFile1Result,fstream::out);
    clean2.open(ICAInputFile2Result,fstream::out);
    clean3.open(ICAInputFile3Result,fstream::out);

    //check for opening file errors
    if((clean1.fail())||(clean2.fail())||(clean3.fail())){

      MessageBox(NULL,TEXT ("Error in opening OUTPUT file"),
      TEXT("EracleFastICA"),MB_OK);

    }

    /*split the clean matrix in 3 different file,
    that will be opened by EracleRMS,
    each sample is separated by a white space.
    If input matrix is uscitaT -->>>>
          the "mean corrected" values are printed
    If input matrix is clean -->>>>
          the raw values returned by apply are printed*/
    for(int r=0; r<DIM_CHANNEL; r++){
      clean1<<uscitaT.at(r,0);
      clean1<<" ";
      clean2<<uscitaT.at(r,1);
      clean2<<" ";
      clean3<<uscitaT.at(r,2);
      clean3<<" ";
    }

    /*close files and streams*/

    clean1.close();
    clean2.close();
    clean3.close();

    fastica_stream.close();

    fclose(Mazinga1);
    fclose(Mazinga2);
    fclose(Mazinga3);


  //flush of ostringstream
  ossICA.str("");
  ossICA.clear();
```

```
    indiceICA++; //loop variable++

    pippo.~fastICA();
    constTransfMatrix.~matrix();
    sourceT.~matrix();
    source.~matrix();
    cleanT.~matrix();
    clean.~matrix();
    uscita.~matrix();
    uscitaT.~matrix();

  }


  MessageBox(NULL, TEXT("End of FastICA"),
  TEXT("EracleFastICA"), MB_OK);



  return;
}
```

A.4 Eracle RMS

```
/*******************************************************
EracleRMS.cpp:
*
For each acquisition opens the the three output files
generated by FastICAand compute RMS for each of them.
At the end of run there are 3*NUM_ACQ values of RMS
stored in file RMS.txt in Eracle_RMS.
These values will be used to train the NN.
*******************************************************/

#include "stdafx.h"
#include "Eracle.h"
#include <iostream>
#include <string>
#include <fstream>
#include <sstream>

#include "ltiMatrix.h"
#include "s2ws.h"


using namespace std;


#define MAX_LOADSTRING 100

//movement repetitions
#define NUM_ACQ 10

//number of sampled data
#define DIM_CHANNEL 1010


void EracleRMS(){

  MessageBox(NULL, TEXT("Begin of RMS"),
             TEXT("EracleRMS"), MB_OK);

  int indiceRMS = 1;

  ostringstream ossRMS;

  //output filestream
```

```
fstream RootMeanSquare;
RootMeanSquare.open(
      "\\Storage Card\\Eracle_RMS\\RMS.txt",
      fstream::out);

while(indiceRMS<=NUM_ACQ){

  /*open files created by fastICA,
  read the formatted value (double)
  and fill a matrix,
  one column for each channel*/

  string RMSInputPrefix =
    "\\Storage Card\\Eracle_FastICA\\Acq";

  ossRMS<<indiceRMS;
  string RMSNumFile = ossRMS.str();

  string RMSInput1 = "\\Clean1_ICA.txt";
  string RMSInput2 = "\\Clean2_ICA.txt";
  string RMSInput3 = "\\Clean3_ICA.txt";

  string RMSInput1Path = RMSInputPrefix +
                         RMSNumFile + RMSInput1;
  string RMSInput2Path = RMSInputPrefix +
                         RMSNumFile + RMSInput2;
  string RMSInput3Path = RMSInputPrefix +
                         RMSNumFile + RMSInput3;

  FILE * source1;
  FILE * source2;
  FILE * source3;

  source1=fopen (RMSInput1Path.data(),"r");
  source2=fopen (RMSInput2Path.data(),"r");
  source3=fopen (RMSInput3Path.data(),"r");

  /*check for files opening error*/
  if ((source1==NULL)||
    (source2==NULL)||
    (source3==NULL)||
    (RootMeanSquare.fail())) {
    MessageBox(NULL,TEXT ("Error in opening input files"),
    TEXT("EracleRMS"),MB_OK);
```

```
}

/*one array for each source,
and a global vector that will
be use to fill the matrix*/
double source1_data[DIM_CHANNEL];
double source2_data[DIM_CHANNEL];
double source3_data[DIM_CHANNEL];
double source_tot[DIM_CHANNEL*3];



//copy data from files to vectors
for(int k=0;k<DIM_CHANNEL;k++){
  fscanf(source1, "%lf", &source1_data[k]);
  fscanf(source2, "%lf", &source2_data[k]);
  fscanf(source3, "%lf", &source3_data[k]);
}


/*check equal and fixed number
of data acquired, exit if different*/
if( (sizeof(source1_data)/sizeof(double)!=DIM_CHANNEL)||
  (sizeof(source2_data)/sizeof(double)!=DIM_CHANNEL)||
  (sizeof(source3_data)/sizeof(double)!=DIM_CHANNEL)){

  MessageBox(NULL,TEXT ("Array size error"),
             TEXT("EracleRMS"),MB_OK);
  exit(0);

}

//fill the global vector
int i;

for(i=0;i<DIM_CHANNEL;i++){
  source_tot[i]= source1_data[i];
}


for(i=DIM_CHANNEL;i<DIM_CHANNEL*2;i++){
  source_tot[i]=source2_data[i-DIM_CHANNEL];
}
```

```
for(i=DIM_CHANNEL*2;i<DIM_CHANNEL*3;i++){
  source_tot[i]=source3_data[i-DIM_CHANNEL*2];
}



/*matrix creation: 3 rows (one per source)
and DIM_CHANNEL column*/
lti::matrix<double> clean_source(3,DIM_CHANNEL,
                                 source_tot);



/*apply the formula:

  sqrt((1/DIM_CHANNEL)*SUM(i=0,i=DIM_CHANNEL)[Si^2])

for each column of the matrix
generated by EracleFastICA function.

The value of RMS are stored in a file,
separated by a blank spaces*/

double RMS;
double sumOfSquare=0;

for(int ch=0; ch<3;ch++){

  for(int k=0;k<DIM_CHANNEL;k++){
    sumOfSquare=sumOfSquare+
    pow(clean_source.at(ch,k),2);
  }

  RMS = sqrt(sumOfSquare/DIM_CHANNEL);

    RootMeanSquare<<RMS*100;
    RootMeanSquare<<" ";


  RMS=0;
  sumOfSquare=0;
}
```

```
    fclose(source1);
    fclose(source2);
    fclose(source3);


    //flush of ostringstream
    ossRMS.str("");
    ossRMS.clear();

    indiceRMS++; //loop variable ++
  }


  RootMeanSquare.close();

  MessageBox(NULL,TEXT ("End of RMS calculation"),
  TEXT("EracleRMS"),MB_OK);

  return;
}
```

A.5 Eracle Neural Network Train

```
/*********************************************************
EracleNeuralNetworkTRAIN.cpp:
*
Open the (number of movement, actually 6)
files in Eracle_NN
containing each NUM_ACQ*3 root mean square.
These values are employed to train an Artificial
Neural Network that will
be used to recognize the user's movement.
The NN is saved in EracleNN in TrainedNN.dat
*********************************************************/

#include "stdafx.h"
#include "Eracle.h"
#include <iostream>
#include <string>
#include <fstream>
#include <sstream>
#include <ltiMLP.h>
#include <ltiLispStreamHandler.h>
#include "ltiRbf.h"
using namespace std;


#define MAX_LOADSTRING 100

//number of repetitions
#define NUM_ACQ 10

//number of samples
#define DIM_CHANNEL 1010

void EracleNeuralNetworkTRAIN(){

  fstream nnTrain;
  nnTrain.open("\\Storage Card\\Eracle_NN\\nnTrain.txt",
  fstream::out);

  /*(((1)))
  open the 6 files with the movement RMS:*/


  FILE* mov0;
```

```
FILE* mov1;
FILE* mov2;
FILE* mov3;
FILE* mov4;

mov0=fopen("\\Storage card\\Eracle_NN
            \\RMSmov0.txt","r");
mov1=fopen("\\Storage card\\Eracle_NN
            \\RMSmov1.txt","r");
mov2=fopen("\\Storage card\\Eracle_NN
            \\RMSmov2.txt","r");
mov3=fopen("\\Storage card\\Eracle_NN
            \\RMSmov3.txt","r");
mov4=fopen("\\Storage card\\Eracle_NN
            \\RMSmov4.txt","r");



/*(((2)))
fill the global array reading from each file*/

//examples data array for training
double RMSglobal [((NUM_ACQ)*3)*5];

//answer data array for training
int RMSanswer [NUM_ACQ*5];



//fill each input vector with data from corresponding file

//((NUM_ACQ)*3) RMS for mov0
for(int k=0;k<((NUM_ACQ)*3);k++){
  fscanf(mov0, "%lf", &RMSglobal[k]);
}

//((NUM_ACQ)*3) RMS for mov1
for(int k=((NUM_ACQ)*3);k<(((NUM_ACQ)*3)*2);k++){
  fscanf(mov1, "%lf", &RMSglobal[k]);
}

//((NUM_ACQ)*3) RMS for mov2
for(int k=(((NUM_ACQ)*3)*2);k<(((NUM_ACQ)*3)*3);k++){
  fscanf(mov2, "%lf", &RMSglobal[k]);
}
```

```
//((NUM_ACQ)*3) RMS for mov3
for(int k=(((NUM_ACQ)*3)*3);k<(((NUM_ACQ)*3)*4);k++){
  fscanf(mov3, "%lf", &RMSglobal[k]);
}

//((NUM_ACQ)*3) RMS for mov4
for(int k=(((NUM_ACQ)*3)*4);k<(((NUM_ACQ)*3)*5);k++){
  fscanf(mov4, "%lf", &RMSglobal[k]);
}

//examples matrix for training
lti::dmatrix train_matrix (5*NUM_ACQ,3,RMSglobal);


//fill the answer training vector

int i;

//NUM_ACQ rms represent mov0
for(i=0; i<NUM_ACQ; i++)
  RMSanswer[i]=0;

//NUM_ACQ rms represent mov1
for(i = NUM_ACQ; i<NUM_ACQ*2;i++)
  RMSanswer[i]=1;

//NUM_ACQ rms represent mov2
for(i = NUM_ACQ*2; i<NUM_ACQ*3;i++)
  RMSanswer[i]=2;

//NUM_ACQ rms represent mov3
for(i = NUM_ACQ*3; i<NUM_ACQ*4;i++)
  RMSanswer[i]=3;

//NUM_ACQ rms represent mov4
for(i = NUM_ACQ*4; i<NUM_ACQ*5;i++)
  RMSanswer[i]=4;

//answer vector for training
lti::ivector train_results_vector (NUM_ACQ*5,RMSanswer);

//object NN
lti::MLP ann;
```

```
  //NN parametersss
  lti::MLP::parameters param;
  lti::MLP::sigmoidFunctor sigmoid(1);
  param.setLayers(12,sigmoid);
  param.trainingMode=lti::MLP::parameters::SteepestDescent;
  param.maxNumberOfEpochs=2000;
  param.learnrate=0.01;
  //param.momentum=1.0;
  //param.stopError=0.002;
  ann.setParameters(param);


  MessageBox(NULL,TEXT("Begin of training"),
             TEXT("EracleNeuralNetworkTRAIN"),MB_OK);

  ann.train(train_matrix,train_results_vector);

  MessageBox(NULL,TEXT("End of training"),
             TEXT("EracleNeuralNetworkTRAIN"),MB_OK);


  ofstream recNN ("\\Storage Card\\Eracle_NNù
                   \\TrainedNN.dat");

  lti::lispStreamHandler lsh(recNN);

  ann.write(lsh);

  recNN.close();


  MessageBox(NULL,TEXT("Trained NN saved"),
  TEXT("EracleNeuralNetworkTRAIN"),MB_OK);

  fclose(mov0);
  fclose(mov1);
  fclose(mov2);
  fclose(mov3);
  fclose(mov4);
  //fclose(mov5);


  return;
}
```

A.6 Eracle Neural Network Classify

```
/*********************************************************
EracleRecognizer.cpp:
*
read the previous data acquired corresponding to a
single movement to be classified.
Data are splitted in three files: Parser_Ch1.txt,
Parser_Ch2.txt, Parser_Ch3.txt.
Then they are computed by fastica, the unmix matrix is
computed and directly used in fastica processing.
Fastica output vectors are used to calculate rms of the
input movement, then they are passed to the prevoiusly
trained NN, which classify the movement performed.
The ouput rms and the nn answer are saved in Rec.txt.
All handled files are stored in
\\Storage Card\\Eracle_Recognizer
*********************************************************/



#include "stdafx.h"
#include "s2ws.h"
#include <fstream>

#include "ltiVector.h"
#include "ltiMatrix.h"
#include "ltiFastICA.h"
#include <ltiMLP.h>
#include <ltiLispStreamHandler.h>
#include "ltiRbf.h"
#define MAX_LOADSTRING 100
#define DIM_CHANNEL 1010

using namespace std;


  //variable for result index
  int id;



void EracleRecognizer(){
```

```
  /*file stream for global function output*/
  fstream recognizer;
  recognizer.open("\\Storage Card\\Eracle_Recognizer
                  \\Rec.txt",fstream::out);

  if(recognizer.fail()){
    MessageBox(NULL, TEXT("Error in opening output file"),
               TEXT("eracleParser"), MB_OK);
    exit(0);
  }


/*(((1))) Data parser*****************************************/

  int posD=0;

  fstream Channel_1, Channel_2, Channel_3;

  Channel_1.open("\\Storage Card\\Eracle_Recognizer
                 \\Parser_Ch1.txt",fstream::out);
  Channel_2.open("\\Storage Card\\Eracle_Recognizer
                 \\Parser_Ch2.txt",fstream::out);
  Channel_3.open("\\Storage Card\\Eracle_Recognizer
                 \\Parser_Ch3.txt",fstream::out);

  if(Channel_1.fail()||Channel_2.fail()||Channel_3.fail()){
    MessageBox(NULL, TEXT("Error in opening parser output file"),
               TEXT("eracleParser"), MB_OK);
    exit(0);
  }

  //input stream to get data
  fstream input_data;

  /*the string that will contain all the emg
  board's output (file DATA.txt)*/
  string tot = "";

  //open stream to read data file
  input_data.open("\\Storage Card\\Eracle_Recognizer
                  \\DATI.txt", fstream::in);
  if(input_data.fail()){
    MessageBox(NULL, TEXT("Error in opening data input file"),
    TEXT("eracleParser"), MB_OK);
    exit(0);
```

```
  }



  /*read all the data in input stream
  and store them in string tot*/
  while(input_data.good()){
    getline(input_data,tot);
  }


/****************************************
BEGIN OF PARSING ************************
****************************************/


/*(((1))) replace newline and carriage return with spaces*/

  replace(tot.begin(), tot.end(), '\r', ' ');
  replace(tot.begin(), tot.end(), '\n', ' ');



/*(((2))) find and erase spurious input
vector at the begin of data*/

  //find the position of the first D
  posD=tot.find("D");

  //if file doesn't begin with D...
  if(posD!=0){

  //... erase alla charachters before D
    tot.erase(0,posD);
  }



/*(((3))) delete the last input vector, to prevent
spurious data at the end of stream*/

  size_t ultimo;
  size_t fine;

  //get the position of last D...
```

```
  ultimo = tot.rfind("D");

  //... and the position of the terminator
  fine = tot.rfind("\0");

  //delete last row, but don't erase "\0" charachter
  tot.erase(ultimo, fine-1);



/*((((4)))) count the number of D
      --> this is also the number of rows
      --> this is also the number of "good" data acquired*/


  //numbers of "clean" data acquired
  int conteggio = count(tot.begin(),tot.end(),'D');

  if(conteggio<1010){
    MessageBox(NULL, TEXT("Pochi campioni"),
    TEXT("eracleParser"), MB_OK);
    exit(0);
  }


/*(((5))) split string tot in three files,
 each column to a file, each data separated
 by a blank spaces (included the last one)*/

  size_t begin,end;

  //get the indeces of the first number in first row
  begin = tot.find("D");
  end = tot.find(" ");

  int index;

  int row_count=0;

  //run until 1010 lines have been parsed
  while(row_count < DIM_CHANNEL){

    //for the first number indeces have already been acquired
    if(row_count>0){
      begin = tot.find("D",end);
```

```
      end = tot.find(" ",begin+1);
    }


      //first number of the triple --> to file Channel_1
      for( index = static_cast<int>(begin)+2;
           index<static_cast<int>(end);index++){
        Channel_1<<tot[index];
      }
      Channel_1<<" ";

      //adjust indeces
      begin = tot.find(" ",end);
      end = tot.find(" ",begin+1);

      //second number of the triple --> to file Channel_2
      for(index = static_cast<int>(begin)+1;
          index<static_cast<int>(end);index++){
        Channel_2<<tot[index];
      }
      Channel_2<<" ";

      //adjust indeces
      begin = tot.find(" ",end);
      end = tot.find(" ",begin+1);

      //last number of the triple --> to file Channel_3
      for(index = static_cast<int>(begin)+1;
          index<static_cast<int>(end);index++){
        Channel_3<<tot[index];
      }
      Channel_3<<" ";


    row_count++;
  }


  /*close all streams*/
  input_data.close();

  Channel_1.close();
  Channel_2.close();
  Channel_3.close();
```

```
/*(((2))) FASTICA ***************************************/


  /*unmix matrix is computed on the (unique) movement
  acquired and it is applied to the same set of data*/
  lti::matrix <double> constTransfMatrix;
  lti::fastICA<double> pippo;


  fstream fastica_stream; //stream for summary operations

  /*input files; one for each channel,
  these files are produced by EracleParser() function*/
  FILE * Mazinga1;
  FILE * Mazinga2;
  FILE * Mazinga3;


  //open summary filestream
  fastica_stream.open("\\Storage Card\\Eracle_Recognizer
                       \\FastICA.txt", fstream::out);

  /*check for stream opening error*/
  if (fastica_stream.fail()){
    MessageBox(NULL,TEXT ("Error in opening filestream"),
               TEXT("EracleFastICA"),MB_OK);
    exit(0);
  }

  Mazinga1=fopen ("\\Storage Card\\Eracle_Recognizer
                   \\Parser_Ch1.txt","r");
  Mazinga2=fopen ("\\Storage Card\\Eracle_Recognizer
                   \\Parser_Ch2.txt","r");
  Mazinga3=fopen ("\\Storage Card\\Eracle_Recognizer
                   \\Parser_Ch3.txt","r");

  if ((Mazinga1==NULL)||
    (Mazinga2==NULL)||
    (Mazinga3==NULL)) {/*check for files opening error*/
    MessageBox(NULL,TEXT ("Error in opening Fastica input file"),
               TEXT("EracleFastICA"),MB_OK);
    exit(0);
```

```
}

/*data array declarations -
one per channel - and the "global" array tot*/
double ch1_data[DIM_CHANNEL];
double ch2_data[DIM_CHANNEL];
double ch3_data[DIM_CHANNEL];
double ICAtot[DIM_CHANNEL*3];


//copy data from files to vectors
for(int k=0;k<DIM_CHANNEL;k++){
  fscanf(Mazinga1, "%lf", &ch1_data[k]);
  fscanf(Mazinga2, "%lf", &ch2_data[k]);
  fscanf(Mazinga3, "%lf", &ch3_data[k]);
}


/*check equal and fixed number
of data acquired, exit if different*/
if((sizeof(ch1_data)/sizeof(double)!=DIM_CHANNEL)||
  (sizeof(ch2_data)/sizeof(double)!=DIM_CHANNEL)||
  (sizeof(ch3_data)/sizeof(double)!=DIM_CHANNEL)){

  MessageBox(NULL,TEXT ("Array size error"),
             TEXT("EracleFastICA"),MB_OK);
  exit(0);

}


//fill the tot vector
int i;

for(i=0;i<DIM_CHANNEL;i++){
  ICAtot[i]= ch1_data[i];
}


for(i=DIM_CHANNEL;i<DIM_CHANNEL*2;i++){
  ICAtot[i]=ch2_data[i-DIM_CHANNEL];
}
```

```
  for(i=DIM_CHANNEL*2;i<DIM_CHANNEL*3;i++){
    ICAtot[i]=ch3_data[i-DIM_CHANNEL*2];
  }



  /*matrix creation: 3 rows (one per source)
  and DIM_CHANNEL columns*/
  lti::matrix<double> source(3,DIM_CHANNEL,ICAtot);
  lti::matrixi<double> W,clean;



  //for fastICA rows and cols must be transposed:
  /*after transpose
  each ROW is an acquisition(input vector),
  so it contains one sample for each source
  each COL is the set of data acquired
  by a single channel
      CH1 CH2 CH3
    iV1   |   |   |
    iV2   |   |   |
     .    |   |   |
     .    |   |   |
     .    |   |   |
  */
  lti::matrix<double> sourceT;
  sourceT.transpose(source);


//+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++
//*REMMEAN:
//compute the mean of each channel (column)
//and subtract it from the data
//before passing them to fastica*/

    double mean[3];
    double temporale=0;

    for(int j=0;j<3;j++){

      for(int i=0; i<DIM_CHANNEL; i++){
        temporale = temporale+sourceT.at(i,j);
      }
```

```
      mean[j]=temporale/DIM_CHANNEL;

    temporale = 0;
    }


    lti::matrix<double> media(1,3,mean);


    const double init =1;
    lti::matrix<double> ones(DIM_CHANNEL,1,init);

    lti::matrix<double> matmedia;

    matmedia.multiply(ones,media);

    sourceT.subtract(matmedia);


//+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++


  /*getOffsetVector returns the mean
  of each channel of the input data*/
  lti::vector<double> vec;
  pippo.getOffsetVector(vec);


  /*compute the transformation matrix
  and apply it to the same set of data*/
  if(!(pippo.apply(sourceT,clean))){
    MessageBox(NULL,TEXT("Impossibile eseguire FASTICA"),
    TEXT("Eracle REC"),MB_OK);
    return;
  }


  pippo.getTransformMatrix(constTransfMatrix);


  /*****************************************************

  uscita = W * unmixedsig +
           (W * mixedmean) * ones (1,NumOfSamples);
```

```
*****************************************************/

lti::matrix<double> primoMembro;

lti::matrix<double> cleanT;
cleanT.transpose(clean);
primoMembro.multiply(constTransfMatrix,cleanT);


lti::vector<double> v;
pippo.getOffsetVector(v);
constTransfMatrix.multiply(v);

double appoggio[3];
for(int h=0;h<3;h++){ //traposta "casereccia"
  appoggio[h]=v.at(h);
}

lti::matrix<double> appoggioMatrice (3,1,appoggio);

//unii=ones(1,DIM_CHANNEL)
const double inival =1;
lti::matrix<double> unii(1,DIM_CHANNEL,inival);

lti::matrix<double> secondoMembro;
secondoMembro.multiply(appoggioMatrice,unii);


//uscita = primoMembro + secondoMembro
lti::matrix<double> uscita,uscitaT;
uscita = primoMembro+secondoMembro;

uscitaT.transpose(uscita);

/*******************************************************/


fastica_stream.close();

fclose(Mazinga1);
fclose(Mazinga2);
fclose(Mazinga3);
```

```
/*(((4))) RMS dati*********************************************/


  /*apply the formula:

    sqrt((1/DIM_CHANNEL)*SUM(i=0,i=DIM_CHANNEL)[Si^2])

  for each column of the matrix generated by
  EracleFastICA function.

  The value of RMS are stored in a file,
  separated by a blank spaces*/

  /*RMS is computed on the MEAN CORRECTED data,
  if you want to use the output fastica data
  just swap uscita with clean*/

  double RMS;
  double sumOfSquare=0;
  double NN_class_data[3];

  for(int ch=0; ch<3;ch++){

    for(int k=0;k<DIM_CHANNEL;k++){
      sumOfSquare=sumOfSquare+
      pow(uscita.at(ch,k),2);
    }

    RMS = sqrt(sumOfSquare/DIM_CHANNEL);

    NN_class_data[ch]=RMS*100;

    RMS=0;
    sumOfSquare=0;
  }



//  MessageBox(NULL,TEXT ("End of RMS calculation"),
              TEXT("EracleRMS"),MB_OK);
```

```
//  MessageBox(NULL,TEXT ("EracleRMS\nTUTTO OK"),
                TEXT("EracleFastICA"),MB_OK);



/*((((4))) NN classify*****************************************/


  /*acquire the info of the previously trained NN*/

  lti::MLP annc;


  std::ifstream inNN("\\Storage Card\\Eracle_NN
                      \\TrainedNN.dat");
    lti::lispStreamHandler lsh_c(inNN);

  if(!(annc.read(lsh_c))){
    MessageBox(NULL,TEXT("Error opening NN"),
                TEXT("Eracle NN"),MB_OK);
    exit(0);
  }

  inNN.close();

  //result generated by NN
  lti::MLP::outputVector risultato;


  //vector containing the feature to classify
  lti::dvector feature_to_classify(3,NN_class_data);

  recognizer<<feature_to_classify;


  //classification with NN
  if(!(annc.classify(feature_to_classify,risultato))){
    MessageBox(NULL,TEXT("Impossibile classificare"),
    TEXT("Eracle REC"),MB_OK);
  }

  recognizer<<risultato;

  risultato.getId(risultato.getWinnerUnit(),id);
  recognizer<<id;
```

```
/*switch between possible classification results*/
switch(id){

  case 0:
    MessageBox(NULL,TEXT("Chiusura"),
               TEXT("Eracle REC"),MB_OK);
    break;

  case 1:
    MessageBox(NULL,TEXT("Dorsi"),
               TEXT("Eracle REC"),MB_OK);
    break;

  case 2:
    MessageBox(NULL,TEXT("Palm"),
               TEXT("Eracle REC"),MB_OK);
    break;

  case 3:
    MessageBox(NULL,TEXT("Apertura"),
               TEXT("Eracle REC"),MB_OK);
    break;

  case 4:
    MessageBox(NULL,TEXT("Pointer"),
               TEXT("Eracle REC"),MB_OK);
    break;

}

recognizer.close();



id=0; //reset result index
annc.~MLP(); //destruct NN
feature_to_classify.~vector();
lsh_c.~lispStreamHandler();

return;
}
```

Appendix B

Basic principles of EMG

Electromyogram (EMG) are biometric signals generated by muscles during a contraction.
The *motor unit* is the elementary functional unit of each muscle, it is composed by a spinal motor neuron (called α-motoneuron) and by the corresponding muscle fibers.
The motor command that activates the movement is generated by the brain and it is transmitted through the motor neurons; once this signal is received by the corresponding muscular fibers a contraction is executed. The contraction generates a magnetic field, whose temporal excursion is called *activation potential*. Figure B.1 depicts how the EMG signal is generated and trasmitted through the motor nerve.
The amplitude of EMG signal is directly proportional to the diameter of the muscle.
The sum of the signals generated by all the muscular fiber of a motor unit is called *Motor Unit Action Potential*. This value could easily be detected with an electrode, either a needle one (mainly employed in biomedical field) or a surface electrode like the ones used in electro stimulators.

The main drawback in using surface electrodes is that the signal amplitude and the depth of the motor unit are inversely proportional. It means that the signal recorded is mainly generated by the motor units located near the electrode, while the activation potential of a muscle that is too far (or too deep) will be ignored. This observation entails that the EMG signals sampled from the user's skin are the MUAP generated by the motor unit near the electrode.
This kind of biometric signals has a probability density that is close to Gaussian. The typical frequency of EMG signal is between 15Hz and 150 Hz. The amplitude of EMG signals depends on the muscle under observation; usually it is a value between $50\mu V$ and 20/30mV.

The main noise source in EMG signal processing is *crosstalking*. A single muscle contraction is the result of several motor units working together, this means that a single movement generates many MUAP. Crosstalking is the overlap of action potential generated by different motor unit. In biomedical field this problem is

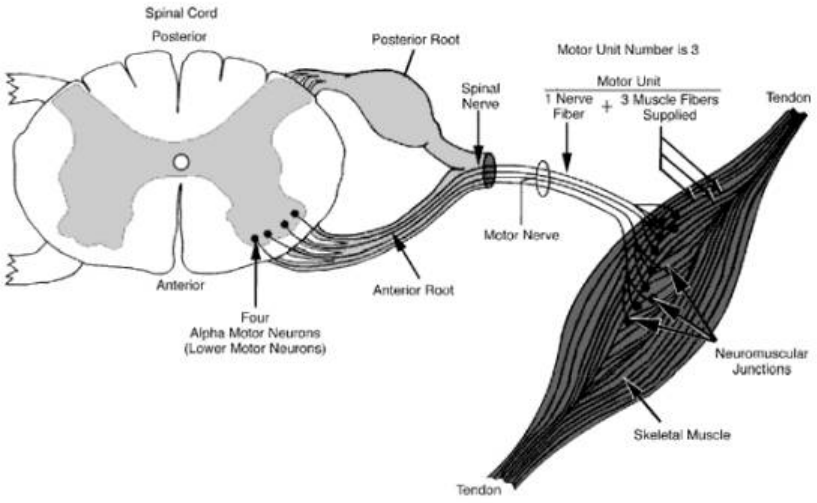

Figure B.1: Schema of EMG signal genesis. The motor command generated by the brain is transmitted through the motor nerve. Once it reach the motor unit a contraction is performed, that generates the activation potential.

avoided employing needle electrodes that are directly inserted into the muscle that must be analyzed. However, needle electrodes are not suitable for an HCI application, so they are replaced by surface electrodes; it entails that the signal processing stage will provide the appropriate signal filtering to remove crosstalking.
Another noise source in EMG signal processing is due to the 50 Hz (or 60 Hz) frequency interference from the mains. This kind of noise can't be completely removed, as its frequency is fully included in the EMG signal bandwidth.
EMG signal is also affected by physiological factors like muscle fatigue and temperature in sampling area. This two aspects lead to a higher signal's amplitude and a shifting of signal's bandwidth towards lower frequencies. As described in [52], there are some corrective formulas that could be applied during the processing stage to partially counteract the negative effects of these factors. In medical fields, EMG

Figure B.2: Positive Sharp Wave, this EMG pattern is usually indicative of muscular injuries [20]

signal analysis is mainly employed to identify some muscular or nerve diseases. For example, figure B.2 shows a pattern called *Positive Sharp Wave:* the signal has a very sharp positive deflection off the baseline followed by a slower return to the baseline. This pattern is usually indicative of muscular injuries and can easily be detected when a muscle fiber is denervated.

"Success is not final. Failure is not fatal.
The courage to continue is what counts."