POLITECNICO DI MILANO
Facoltà di Ingegneria dell'Informazione
Corso di Laurea in Ingegneria e Design del Suono

Automatic real-time bass transcription system based on Combined Difference Function

Supervisor: Prof. Augusto Sarti
Co-Supervisor: Dr. Massimiliano Zanoni

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"There is no end to learning"
Robert Alexander Schumann

Abstract

Due to the recent worldwide diffusion of internet and audio digital formats, in past few years the amount of multimedia contents highly increased. Our approach to produce, listen to and search for music is consequently changing and a great number of applications to help us in these tasks are proposed. For this reason, researchers' studies in music and technology field becomes more and more important. One of the most relevant field is Music Information Retrieval: the interdisciplinary science of retrieving information from music. One of the most interesting field within MIR is Automatic Music Transcription. That is the process of taking a digital sound waveform and extracting the symbolic information related to the high-level musical structures that might be seen on a score.
This thesis proposes an application for real-time bass transcription from an audio signal. Possible users of the application are both amateur and students with few musical notions and expert musicians. For that reason the application is intended to have an extremely simple to use interface and functionalities. The core of the application is the pitch detection algorithm. We used an algorithm based on the composition of two techniques (YIN and SMSDF) that proposes a new method to estimate the pitch, called Combined Difference Function. The application gives the possibility to plug a bass directly in the computer and perform transcription in real-time. A real-time approach has been chosen to provide the user an instant feedback on the bass line played.

Sommario

Grazie alla recente diffusione mondiale di internet e dei formati audio digitali, negli ultimi anni la quantità di contenuti multimediali è notevolmente aumentata. Di conseguenza, l'approccio alla produzione, all'ascolto e alla ricerca di musica sta cambiando e sempre nuove applicazioni ci aiutano in questo genere di attività. Per queste ragioni, la ricerca nel campo della musica e della tecnologia ha acquisito sempre più importanza. Un settore di ricerca tra i più rilevanti è quello del Music Information Retrieval (MIR). MIR è quella scienza interdisciplinare che si occupa di recuperare informazioni dai brani musicali. Uno degli ambiti più interessanti all'interno di MIR è quello che si occupa di Trascrizione Musicale Automatica. Con trascrizione musicale intendiamo il processo di estrazione, da un segnale audio digitale, di informazioni simboliche relative alle strutture musicali che possiamo vedere in un comune spartito.
Questa tesi propone un'applicazione per la trascrizione del basso in tempo reale partendo da un segnale audio. Possibili fruitori dell'applicazione sono sia studenti e dilettanti, con poche conoscenze musicali, sia musicisti esperti e competenti. Per questa ragione l'applicazione è stata realizzata in modo da essere estremamente semplice da utilizzare sia nell'interfaccia che nelle funzionalità.
Il nucleo dell'applicazione è l'algoritmo di stima dell'altezza della nota (pitch). Per questo compito è stato usato un algoritmo, basato sulla composizione di due diverse tecniche (YIN e SMSDF), che propone un nuovo metodo per stimare l'altezza della nota, chiamato Combined Difference Function. L'applicazione da la possibilità di collegare il basso direttamente nel computer ed effettuare la trascrizione in tempo reale: un approccio di questo tipo è stato scelto per poter dare all'utente un feedback immediato sulla propria esecuzione.

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Abbreviations

ACF	Autocorrelation function
CAMDF	Circular Average Magnitude Difference Function
CMNDF	Cumulative Mean Normalized Difference Function
DF	Difference Function
DFT	Discrete Fourier transform
EM	Expectation-maximization
F0(f0)	Fundamental frequency
FFT	Fast Fourier transform
IDFT	Inverse discrete Fourier transform
MIDI	Musical Instrument Digital Interface
PCM	Pulse Code Modulation
SMSDF	Sum Magnitude Difference Square Function

Chapter 1

Introduction

"An orchestra without a double bass is inconceivable. It is the essential orchestral instrument.
You can almost say that an orchestra set about to exist only when there's a double bass.
There are orchestras with no first violin, no horns, no drums and trumpets, nothing at all.
But not without a double bass.
What I want to establish is that double bass is by far the most important instrument of the orchestra.
Even if it does not seem."

Double Bass - Patrick Süskind

Thanks to the wide diffusion of internet and digital technologies in past few years, our way to approach music is extremely changed. Digital audio players, mp3 files and music software are new tools to interact with music. The way we listen or how we record music is completely different from ten years ago. The availability of musical contents in digital form is exponentially increased and thus the need to organize and provide access. The pressure of consumers has drawn the attention of researchers and industry to this tasks. The large amount of audio material raised new issue on handling and organizing it. A new field in audio research was born: Music Information Retrieval. MIR is the interdisciplinary science of retrieving information from music and includes music classification, feature extraction, database creation, indexing, signal processing, music analysis and music representation. An important area of research within MIR is automatic music transcription. Music transcription is intended as the act of writing down the notes played in a music excerpt, in a coded notation which includes notes, pitch, length and expression. With Automatic Music Transcription we intend the process of transcribing music performed automatically by a computer. In last few years the problem has been easily solved using MIDI protocols and MIDI instrument interfaces (MIDI keyboard, MIDI Drum, MIDI Guitar, etc...). MIDI is a protocol thought to send music messages between MIDI interfaces and no audio signal is transmitted. Messages as note pitch or note starting or ending instant are transmitted: it's easy to store this messages and create, automatically, a transcription of a MIDI performance. Although, MIDI protocols has some limitation in expressivity to describe a performance. For that reason researchers started to focus on more expressive automatic music transcription. The new line to cross is music transcription using content-based methods based on the direct analysis of the audio signal. Automatic music transcription research is divided in two main areas:

- Monophonic transcription: analysis of music instruments that produce only one note at a time, composing a melody;
- Polyphonic transcription: concerns music instruments that can produce more notes at a time, generating chords and or instruments in a polyphonic context (mixed excerpt).

The focus of this thesis is on monophonic instruments and the goal is to realize a real time application for automatic bass transcription. The application is realized for being simple and usable for everyone, from the professional musician to the entry-level music student.

1.1 Background

1.1.1 Automatic transcription

Since ages, one of musicians' hardest work has been music transcription. This is a hard work required of a good "musical ear", that is the capability of discerning a sequence of music notes. Usually, this ability comes with years of study, practice and exercises. But, nowadays, the help of technology and the rising of the research in the audio-music field let the musicians be helped by software applications and algorithms capable of automatic transcription. This applications open wides scenarios for the professional musician as well as for the student and for the casual user. In Figure 1.1 we can see a general scheme of automatic transcription: from an audio signal we retrieve all the information needed to generate a music score. Automatic music transcription (expression coined in first works in this field by Moorer [1] and

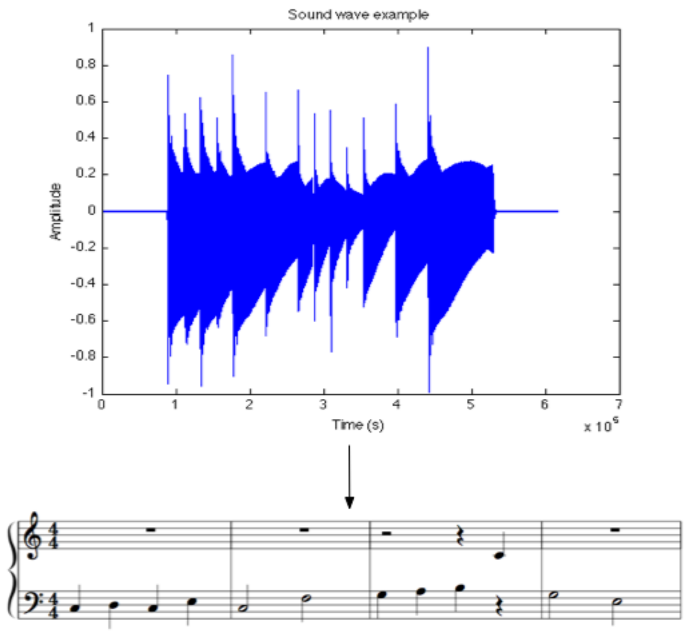


Figure 1.1: Acoustic signal to score notation

by Piszczalski and Galler [2]) is the process through music transcription is performed by an algorithm. Generally, someone with no musical education, can't figure out a song's score and, to tell the truth, this process comes to be hard for who has this education too. The richer is the polyphonic complexity of a musical composition, the more experience is needed in the musical style and the instruments in question, and in music theory. The positive aspect of Automatic Music Transcription could be:

- to helps researchers and musicians to learn all the musical aspect, like the harmony, structure, chord progression or single notes, of a song;
- it can give a less space consuming representation of music: a score or an xml file occupy less than a mp3 file;
- to allows the organization and cataloging of a songs database;
- jam musician can have all performance transcribed on a score;
- to help composer in composition.

Today music transcription algorithms already reached good results in monophonic context, but most of them have high computational complexity. The available applications, also, do not perform automatic music transcription in a real-time fashion. We choose, then, to use simpler and low computational complexity methods in order to implement automatic music transcription in real-time. The purpose of this work is to create a real-time application using state-of-art methods for pitch tracking for bass-guitar instrument.

1.1.2 Electric Bass

The thesis work is based on the electric bass. The bass (or bass guitar) is a stringed instrument played primarily with the fingers or thumb. It is similar in appearance and construction to an electric guitar, but with a longer neck and scale length, and four, five, or six strings. The four string bass, by far the most common, is usually tuned the same as the double bass, which correspond to pitches one octave lower than the four lower strings of a guitar (E, A, D, and G). The bass guitar is a transposing instrument, as it is notated in bass clef an octave higher than it sounds. Since the 1950s, the electric bass guitar has largely replaced the double bass in popular music as the bass instrument in the rhythm section. In Figure 1.2 a typical Fender Jazz bass is shown.

Figure 1.2: Fender Jazz Bass

1.1.3 Fundamental frequency and Pitch

The core of monophonic transcription systems is the fundamental frequency tracking. The fundamental frequency, often referred to simply as the fundamental and abbreviated f0 or F0, is defined as the lowest frequency of a periodic waveform, while pitch represents the perceived fundamental frequency of a sound [5]. Pitch it is one of the major auditory attributes of musical tones along with duration, loudness, timbre, and sound source location. Pitches are compared as ”higher” and ”lower” in the sense that allows the construction of melodies. Pitch may be quantified as a frequency in cycles per second (Hertz - Hz), however pitch is not a purely objective physical property, but a subjective psycho-acoustical attribute of sound. Pitch is related to frequency, but they are not equivalent: frequency is the scientific measure of pitch. While frequency is objective, pitch is completely subjective.

1.2 Brief work description

Each musical note can be described by three essential parameters: the fundamental frequency (pitch), the beginning of a note (onset time), and the note duration. For this reason, a transcription system should include both pitch tracker and onset detector, although not necessarily implemented as two separate blocks. Previous papers tend to describe techniques for pitch and onset detection rather separately, so only few compact and reliable monophonic transcribers were published. In Figure 1.3 an overview of the work is presented.

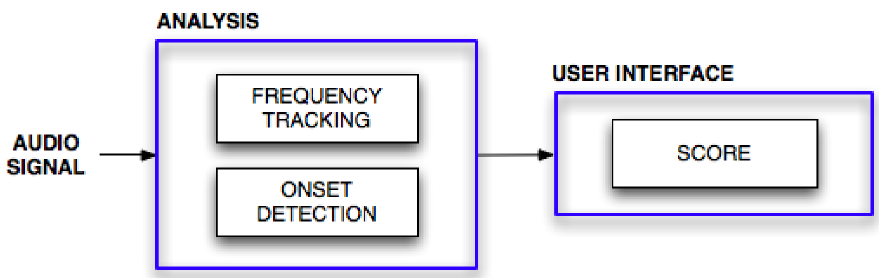


Figure 1.3: Structure of the transcription system

We now introduce each single block that will be further analyzed in the next chapters.

1.2.1 Frequency Tracking

This block concerns the problem of fundamental frequency (f0) estimation. The work is mainly based on two algorithms: the YIN algorithm [4] and the SMDSF one [3]. Both algorithms relies on the difference function, a simple but effective solution for frequency estimation. The frequency tracking block also contributes to the determination of the note onsets and their length.

1.2.2 Onset Detection

Onset detection refers to the detection of the beginning instants of discrete events in the acoustic signals. A percept of an onset is caused by a noticeable change in the intensity, pitch or timbre of the sound. The onset of the note is a single instant chosen to mark the temporally extended transient. In most cases, it will coincide with the start of the transient, or the earliest time at which the transient can be reliably detected.

1.2.3 User Interface

A graphical part for the real-time score visualization is needed. The user interface provides a feedback to the user and let him use the application in a simple way.

1.3 Overview of the thesis

The thesis is organized as follows:

- In chapter 2 we'll take a view of the state of the art of the monophonic automatic music transcription field in research and then we'll have a look of some commercial applications.
- In chapter 3, the algorithm is presented by means of the mathematical background and a complete explanation of its work.
- In chapter 4 the system design details are presented.
- Chapter 5 discuss about the developing of the software application.
- In Chapter 6 we show the results of the application.
- Finally, chapter 7 presents conclusions and guidelines for future improvements and evolutions.

Chapter 2

State of the art

In past few years, audio research and industries made several progress towards achieving the state-of-the-art in automatic music transcription. Many algorithms and applications have been developed. In this section we will discuss about related works from both research and commercial application. The core of monophonic music transcription is the pitch estimation: the first part of this chapter concerns about the most used algorithms for this purpose. Afterward, the most recent applications for automatic monophonic music transcription are considered.

2.1 Algorithms

In this section we describe some fundamental frequency estimation algorithms for monophonic audio, organized by type of input and processing paradigm. In the case of polyphonic audio, with more instruments mixed on a single track, the aim of the algorithms is to extract the single instrument parts (source separation) and transcribe them. In this work we concentrate on the transcription of a bass-line in a monophonic context, so we will not consider algorithm for source separation.
Time domain methods are presented first, as they are usually computationally simple. Frequency domain methods, presented next, are usually more complex. First, a brief excursus on fundamental frequency is proposed.

2.1.1 Fundamental Frequency

As we mentioned in the previous chapter the core of the work is represented by the fundamental frequency estimation. We refer to the fundamental frequency, or f0, as the lowest frequency of a periodic waveform. On the other hand pitch represents the perceived fundamental frequency of a sound. The fundamental frequency is a measurable quantity while pitch is a purely subjective property of the sound. What we need for our work is to estimate the fundamental frequency.

2.1.2 Time-Domain Methods

Time-Event Rate Detection

There is a family of related time-domain F0 estimation methods which looks for the number of repetition of the waveform period. The theory behind these methods relies on the fact that if a waveform is periodic, then some time-repeating events can be retrieved and counted. The number of repetitions that occurs in a second is inversely related to the frequency. Each of these methods is useful for particular kinds of waveforms. In the case of non-periodic waveform this methods are not valid.

Zero-crossing rate (ZCR). The ZCR is a measure of how often the waveform crosses the zero value per unit time. The idea is that the ZCR gives information about the spectral content of the waveform. ZCR has been one of the first technique used from researchers for pitch estimation.The thought is that the ZCR it's directly related to the number of times the waveform repeated per unit time. As Curtis Roads [7] explains, it was soon made clear that there are problems with this measure of F0. In the case of pure sounds, composed of a single sinusoid, the waveform will cross the zero line twice per cycle, as in Figure 2.1a, and it's possible to retrieve its frequency. If the waveform contains higher-frequency spectral components, as pitched

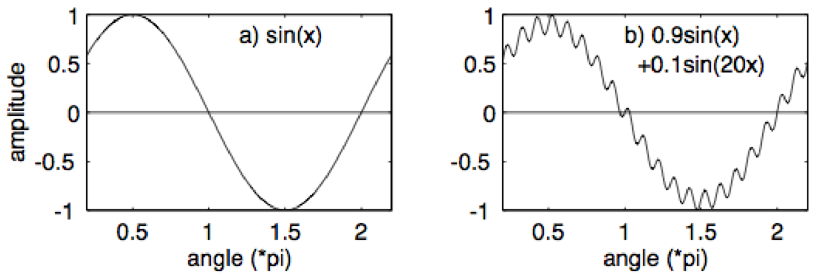


Figure 2.1: Influence of higher harmonics on zero crossing rate

sounds in nature (Fig. 2.1b), then it might cross the zero line more than twice per cycle.

Peak rate. This method counts the number of positive peaks per second in the waveform. In pure sounds, the waveform have a maximum value and a minimum value each cycle, and one needs only to count these maximum values (or minimum values) to determine the frequency of the waveform. In real sounds, a local peak detector must be used to find where the waveform is locally largest, and the number of these local maxima in one second is the frequency of the waveform, unless each period of the waveform contains more than one local maximum. The distance between this local maxima gives the wavelength which is inversely proportional to the frequency. As explained by David Gerhar in his pitch extraction history report [15], peak counters have been the choice of hardware frequency-detectors for many years, because the easiness of the circuit which coupled with a simple low-pass filter, provides a fairly robust module.

The main problems using ZCR and peak rate methods for pitch estimation stand by the fact that real waveforms are never composed of a single sinusoid but, instead, have a complex spectra formed by more partials and, often, by noise. By this fact, waveforms rarely have just one event per cycle: they may cross zero many times or have many peaks in a cycle. In the case of bass transcription these methods are never used because of the bass waveform that consists of a high frequency attack and a harmonically rich spectrum due to the partials superposition.
Nevertheless, there are some positive aspects of these time-event rate detection algorithms. These methods are simple to understand and implement, and they take very little computing power to execute. In case of non-ideal situations or for better performances is better to use more effective algorithms.

Autocorrelation

Autocorrelation method is firstly introduced in speech processing in 1968 by M. Sondhi [8], and then considered as a model in most of the pitch detection works. The autocorrelation method doesn't suffer of problems on the waveform complexity and it is considered one of the most performing algorithm. The correlation between two waveforms is a measure of their similarity. The waveforms are compared at different time intervals, and their likeness is calculated at each interval. The result of a correlation is a measure of similarity as a function of time lag between the beginnings of the two waveforms. The autocorrelation function is the case of the correlation of a waveform with itself. One would expect exact similarity at a time lag of zero, with increasing dissimilarity as the time lag increases. The mathematical definition of the autocorrelation function is shown for a discrete signal x[n] in equation 2.1:

$$R_x(\nu) = \sum x[n]x[n+\nu] \tag{2.1}$$

De Cheveigné and Kawahara [9] noted that as the time lag increases to half of the period of the waveform, the correlation decreases to a minimum. This is because the waveform is out of phase with its time-delayed copy. As the time lag increases again to the length of one period, the autocorrelation again increases back to a maximum, because the waveform and its time-delayed copy are in phase. The first peak in the autocorrelation indicates the period of the waveform. The autocorrelation method has been widely used in pitch detection and also in bass transcription by Ryynänen and Klapuri on their works on bass line transcription [10] [11].

2.1.3 Frequency-Domain Methods

There are a lot of information in the frequency domain that can be related to the fundamental frequency of the signal. Pitched signals tend to be composed of a series of harmonically related partials, which can be identified and used to extract the F0. Many attempts have been made to extract and follow the f0 of a signal in this manner.

Filter-Based Methods

Filters are used for f0 estimation by using different filters with different center frequencies, and comparing their output. When a spectral peak lines up with the passband of a filter, the result is a higher value in the output of the filter than when the passband does not line up.

Comb Filter. The optimum comb f0 estimator by J. A. Moorer [12] is a robust but computationally intensive algorithm. A comb filter has many equally spaced pass-bands. In the case of the optimum comb filter algorithm, the location of the passbands depends on the location of the first passband. For example, if the centre frequency of the first passband is 10 Hz, then there will be narrow pass-bands every 10 Hz after that, up to the Shannon frequency. In his algorithm, the input waveform is comb filtered based on many different frequencies. If a set of regularly spaced harmonics are present in the signal, then the output of the comb filter will be greatest when the passbands of the comb line up with the harmonics. If the signal has only one partial, the fundamental, then the method will fail because there will be many comb filters that will have the same output amplitude, wherever a passband of the comb filter lines up with that fundamental. No papers on comb-filter algorithms used for bass transcription have been found.

IIR Filter. A more recent filter-based f0 estimator is suggested by J. E. Lane in [13]. This method consists of a narrow user-tunable band-pass filter, which is swept across the frequency spectrum. When the filter is in line with a strong frequency partial, a maximum output will be present in the output of the filter, and the f0 can then be read off the centre frequency of the filter. The author suggests that an experienced user of this tunable filter will be able to recognize the difference between an evenly spaced spectrum, characteristic of a richly harmonic single note, and a spectrum containing more than one distinct pitch.

Cepstrum. Cepstrum analysis is a form of spectral analysis where the output is the Fourier transform of the log of the magnitude spectrum of the input waveform. This procedure was early developed by J. L. Flanagan [14] in the attempt to make a non-linear system more linear. Naturally occurring partials in a frequency spectrum are often slightly inharmonic, and the cepstrum attempts to mediate this effect by using the log spectrum. The name cepstrum comes from reversing the first four letters in the word "spectrum", indicating a modified spectrum. The independent variable related to the cepstrum transform has been called "quefrency", and since this variable is very closely related to time, as explained by C. Roads in [7], it is acceptable to refer to this variable as time. The theory behind this method relies on the fact that the Fourier transform of a pitched signal usually has a number of regularly spaced peaks, representing the harmonic spectrum of the signal. When the log magnitude of a spectrum is taken, these peaks are reduced, their amplitude brought into a usable scale, and the result is a periodic waveform in the frequency domain, the period of which (the distance between the peaks) is related to the fundamental frequency of the original signal. The Fourier transform of this waveform has a peak at the period of the original waveform. Figure 2.2 shows the steps of the cepstrum algorithm. Figure 2.2b shows the spectral representation of a periodic harmonic signal. Figure 2.2c shows the log magnitude spectrum of the same signal. While Figure 2.2d shows the final cepstrum of the log magnitude spectrum. Like many other f0 estimation methods, this method is well suited to specific types of signals. It was originally developed for use with speech signals, which are spectrally rich and have evenly spaced partials. Until now, nobody

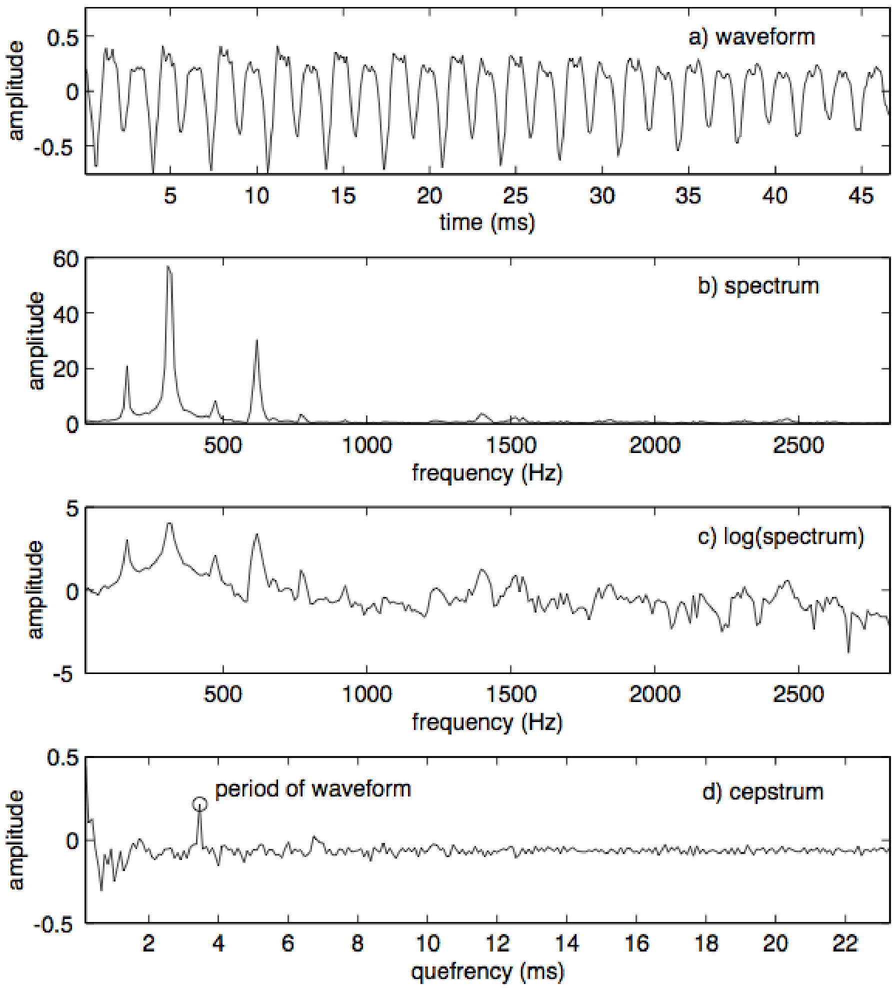


Figure 2.2: Stages in the cepstrum analysis algorithm

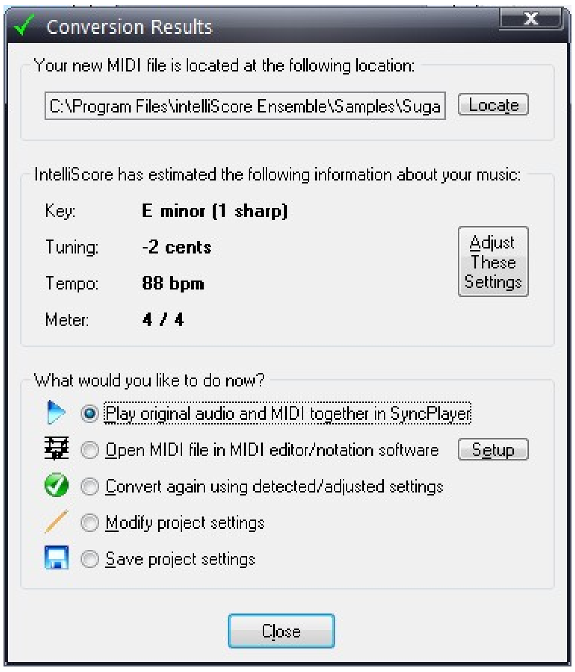
tried to perform bass transcription with the Cepstrum analysis.

2.2 Software Applications

The aim of this thesis is to realize a real-time bass transcription application. As requirement the application user interface is built to be as simple as possible: it should be usable by music students as well as professional musicians. In this section a review of similar applications is presented. Nevertheless, these applications are commercial, built for people with a big experience in music, and significantly different from our work: transcription applications are not in real-time, while real-time applications do not perform transcription. In particular none of the applications is specifically for bass.

2.2.1 MP3 to MIDI converter, by IntelliScore [1]

The mp3 to MIDI converter performs transcription of music from polyphonic audio files into midi files. It helps you create music notation by converting multiple instrument audio to multitrack MIDI files containing the notes played, broken down by instrument. The process is fast but not in real-time. Additionally, it offers the possibility to record a (voice or instrument) performance using the microphone as input source. In Figure 2.3 we can see the user interface of MP3 to MIDI converter. Unlike our application, this software provides both polyphonic and monophonic transcription from audio files but not in real-time. Intelliscore, also, does not offers a score visualization and leave the user the possibility to edit the score with other softwares. From an algorithmic point of view, the underlying technology is


Conversion Results

Your new MIDI file is located at the following location:

C:\Program Files\intelliScore Ensemble\Samples\Suga

IntelliScore has estimated the following information about your music:

Key: E minor (1 sharp)

Tuning: -2 cents

Tempo: 88 bpm

Meter: 4 / 4

What would you like to do now?

[✓ Play original audio and MIDI together in SyncPlayer]

Open MIDI file in MIDI editor/notation software

Convert again using detected/adjusted settings

Modify project settings

Save project settings

Figure 2.3: MP3 to MIDI converter interface, by IntelliScore

unknown and no direct comparison can be done with our work.

[1] Intelliscore MP3 to MIDI converter, http://www.intelliscore.net

2.2.2 Melodyne, by Celemony [2]

Melodyne is one of the most famous and used professional software for pitch correction in recording studios. This software lets you edit your monophonic and polyphonic music excerpts. They propose a technology called Direct Note Access [3] that makes possible to identify and edit individual notes within polyphonic instruments (like piano, guitar,...). It has a mixed time-amplitude-pitch grid where notes are disposed with their waveform. Despite, it does not provide any kind of transcription. And this is the biggest difference with our work. We can not do a direct comparison with respect to our application because of the different goals.

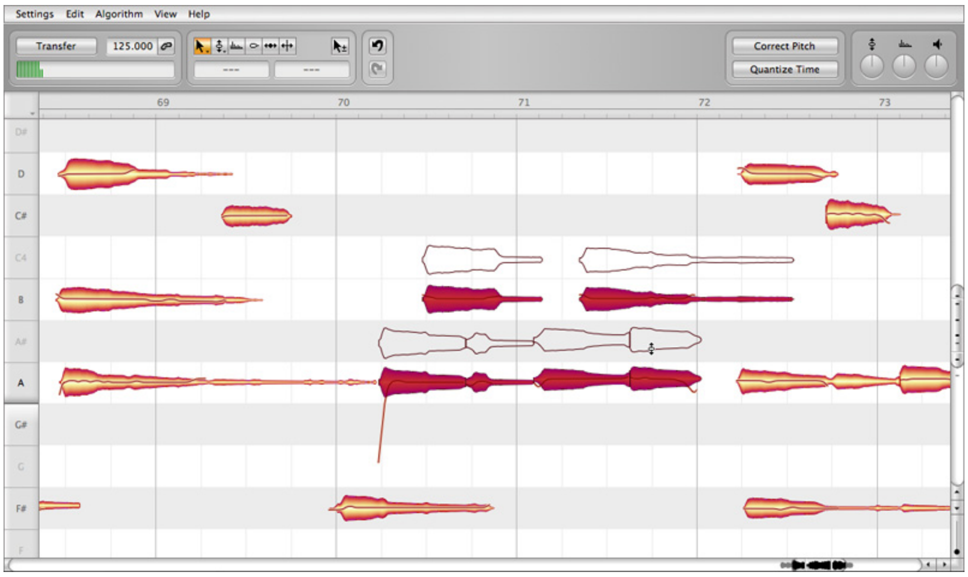


Figure 2.4: Melodyne, by Celemony

2.2.3 Audioscore Ultimate 6, by Neutraron [4]

This software allows to open MP3 files and convert them to a score. It accept polyphonic material as it performs source separation. By using an undisclosed technology it is possible to convert up to 16 instruments / notes playing at a time into multiple staves. It works also with bass, but the processing is not performed in real-time and it does not offers the possibility

[2]Melodyne, by Celemony, http://www.celemony.com
[3]Direct Note Access, http://www.celemony.com/cms/index.php?id=dna
[4]Audioscore 6, http://www.neuratron.com/audioscore.htm

to record and process a live instrument. In figure 2.5 we can see the main user interface of AudioScore Ultimate 6.

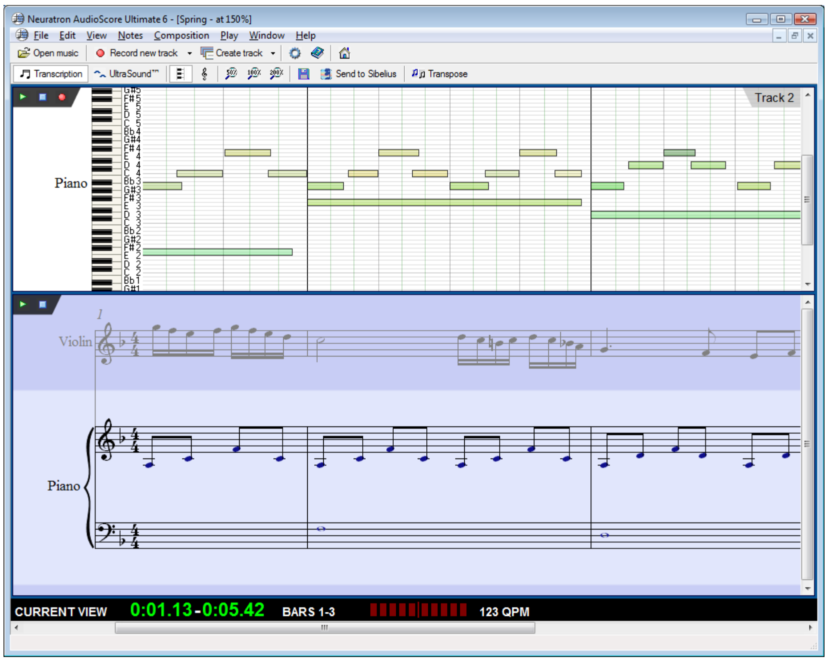


Figure 2.5: Audioscore Ultimate 6, Neuratron.com

2.2.4 Capo, by Supermegaultragroovy [5]

Capo is a software recently developed for assists in the process of transcription guitar tablature. guitar (or bass) transcription. It is well integrated with iTunes library and with Mac OS X. Its strength relies on the ease of use and on a new concept of automatic transcription. Capo elaborates a spectrogram of a song. Selecting a point of it, the system will automatically retrieve the correspondent note, showing it in a window apart. By this fact is completely different from other softwares: it performs a kind of assisted transcription, which is completely different from the entirely-automatic transcription of our application. Capo, again, provides a tablature notation and not a score notation. In tablature notation, notes are denoted by the number of the fret, on the relative string, to be played. It is not a standard notation, but a simpler one, for entry-level guitarists. In figure 2.6 the Capo's user interface is shown.

[5]Capo, http://supermegaultragroovy.com/products/Capo

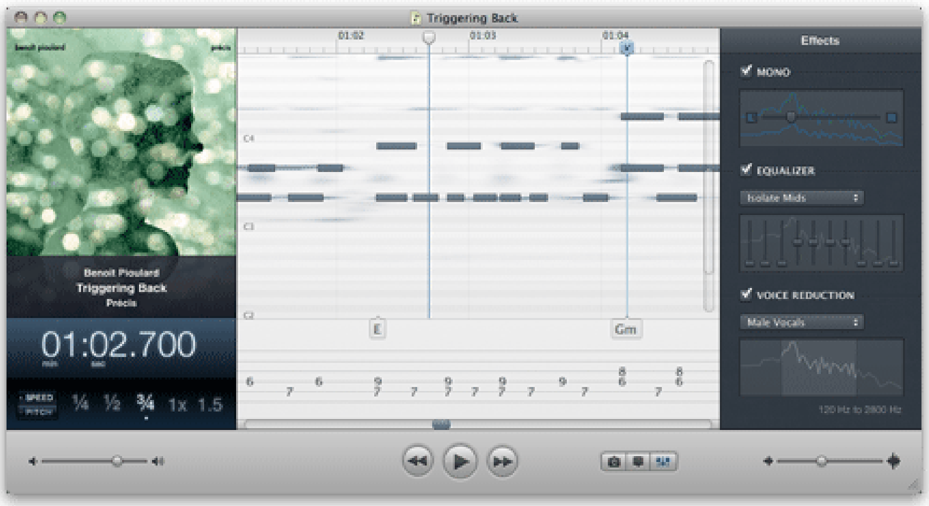


Figure 2.6: Capo, by Supermegaultragroovy

2.2.5 Digital Music Mentor, by Sienzo [6]

We have not many information about this applications, but it is one with an apposite section for bass transcription. Digital Music Mentor performs music transcription from audio files to tablature notation and it works with monophonic audio only. It is not provided any information about the algorithm used for the analysis. The only fact we know is that it does not performs transcription in real-time.

2.2.6 Guitarmaster, by RoboSens [7]

Guitarmaster is another transcription software for automatic guitar transcription. It produces guitar tablature and MIDI files from an audio signal generated by a guitar. It is possible to perform transcription from a live guitar but not in a real-time way: the audio input is recorded and then analyzed. The output of the system it's not a standard score notation but a tablature. The MIDI file can be exported to be opened with another MIDI editing software. Also in this case, no underlying structure is provided. Additionally, it is studied for guitar only and not for bass, to which they do not provide support.

[6]Digital Music Mentor, http://www.sienzo.com
[7]Guitarmaster, http://www.guitarmaster.co.uk/info.htm

Chapter 3

Theoretical Background

As seen in the previous chapters the main issue of monophonic music transcription is the fundamental frequency estimation (F0). Section 3.1 explains the reason of our choice, followed by the description of the algorithm's theory. In the last section we will briefly introduce the MIDI protocol used by our application.

3.1 Introduction

In real world, an audio waveform is composed not of a single sinusoid but by a sum of more overlapping sinusoids. It can be described as a combination of many simple periodic waves (i.e., sinusoids), called partials, each with its own frequency. An harmonic (harmonic partial) is a partials with the frequency multiple of the fundamental frequency. As a pitched instrument, the bass is characterized by the prevalence of harmonic contents. The fundamental frequency (F0) of the waveform can be seen as the harmonic partial with the lowest frequency. Figure 3.1 shows a periodic wave with different partials (harmonics).

3.1.1 Requirements

From the beginning the system was designed to have an instant response to user. Real-time issues came up. There is a trade-off between the accuracy of the algorithm and the latency. A more accurate and effective method needs a more computationally complex algorithm with consequently latency problems. We decided to use a mix of two algorithms, based on simple mathematical structures that gives us the possibility of real-time processing: YIN algorithm [4] and SMDSF [3] algorithm. The SMDSF is an improving of the YIN, and it is based on the Combined Difference Function, that is explained

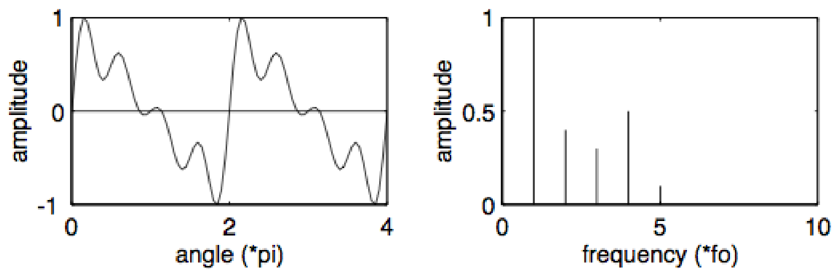


Figure 3.1: Sinusoidal wave with upper harmonics

afterward in this chapter. The YIN is used for the final normalization of the Combined Difference Function.

3.1.2 Bass Constraints

The problem of bass transcription deals with the low frequency values produced. If we consider a single sinusoidal wave, with a certain frequency f, the period T is defined as

$$T = 1/f \tag{3.1}$$

The period value is a measure of the time that it takes for a wave to complete a cycle, and is measured in seconds. The frequency f is the number of periods per unit time (i.e., second) and is typically measured in Hertz (Hz). In signal processing, an audio signal is divided in smaller fixed sized blocks called frames. This facilitates the analysis because of the faster processing on smaller blocks and because it allows a finer resolution on the event calculated.
Given that the frequency is strictly dependent on the period of the waveform, to retrieve it we need to consider a frame longs at least as the period T. Bass produces low frequency notes with long periods. A bass E string is about 41 Hz and its period comes to be about 24ms. In relation ship with other instruments (guitar, voice) this is a very long period. With a sampling frequency of 44.1 KHz we need about 1060 sample, but in base 2 they become 2048 $=2^{11}$. So we need a great number of samples to calculate in a correct way the frequency of our wave. This may cause problems with the real-time implementation because each time we have to wait for the 2048 samples to be collected.

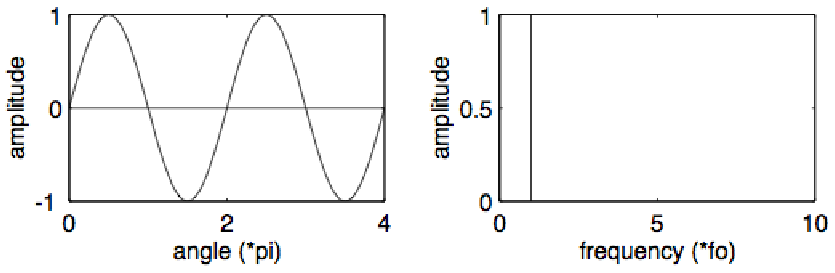


Figure 3.2: A sinusoidal wave

3.1.3 Frequency Estimation Methods

There is a number of standard methods that researchers use to extract F0, based on various mathematical principles. Since pitch is a perceptual quantity related to F0 of a periodic waveform, it should sufficient to determine the period of such oscillation, the inverse of which is the frequency of oscillation. The problem comes when the waveform consists of more than a simple sinusoid, as in our case. A bass note has a complex waveform formed by the result of many components: vibrations produced by the string and the body of the instrument, the way we play the note and the model of the pick-up used. Each of those components add further information, in terms of partials, to the resulting spectra. This makes the F0 estimation a harder task. The goal of a F0 estimator is to find the frequency best harmonically related to the other components of the sound: and usually it is the harmonic with the lowest frequency.
For many years the autocorrelation method has been used, but despite its appeal and many efforts to improve its performance, it still makes too many errors.
A. de Cheveigné and H. Kawahara [4] designed a series of steps for reducing error rates in the autocorrelation method and developed the YIN algorithm based on the Difference Function. Following their choice, L. Jian, T. Fang, D. Jing and W. Wenhu [3] introduced, with their Combined Difference Function, further changes to the YIN algorithm improving its results.

3.2 Algorithm

In the next sections we will introduce some basic concepts about periodic functions and then the mathematical description of the algorithm working is provided.

3.2.1 Difference Function

Given a small portion (frame) of an audio signal x_t, we define it periodic, with period T, as invariant to a time shifting operation with a time-shift value as T:

$$x_t - x_{t+T} = 0, \forall t. \tag{3.2}$$

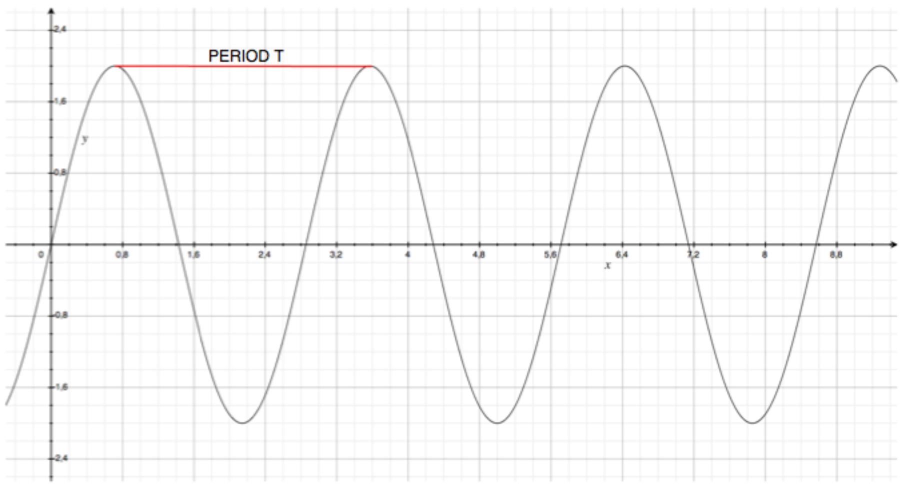


Figure 3.3: A periodic function with period T

Considering x_j as the single sample in the frame we can define:

$$\sum_{j=1}^{N} (x_j - x_{j+T})^2 = 0 \tag{3.3}$$

Conversely, an unknown period may be found by forming the difference function:

$$d_t(\tau) = \sum_{j=1}^{N} (x_j - x_{j+\tau})^2 \tag{3.4}$$

where d_t, denotes the difference function at time index t; x denotes the audio sample sequence; j is the time index (sample point index), N is the size of the analyzed frame; τ is the lag between the two frames.
Our goal is to look for the values of τ for which the function is zero. There is an infinite set of this values, all multiples of the period. We will refer to the equation 3.4 as the Difference Function (DF) or as the Sum Magnitude Difference Square Function (SMSDF).

3.2.2 The YIN algorithm

The YIN F0 estimator [4], developed by Alain de Cheveigne and Hideki Kawahara, takes the name from the oriental yin-yang philosophical principal of balance, representing the authors' attempt to balance autocorrelation and cancellation in the algorithm. One of the main problems of the autocorrelation method is that it can frequently occurs that the intensity of the first harmonic partial is lower then other harmonic partials. In those cases the resulting pitch it's wrongly estimated. YIN attempts to solve this problem in several ways. It is based on the difference function, which, attempts to minimize the difference between the waveform and its delayed duplicate, instead of maximizing the product as autocorrelation does. The difference function is presented in equation 3.4 and it's re-proposed in equation 3.5:

$$d_t(\tau) = \sum_{j=1}^{N} (x_j - x_{j+\tau})^2 \tag{3.5}$$

The calculation of this equation is computationally expensive and two different mathematical solutions have been proposed by YIN [4]: the first based on a recursive technique, the second on the FFT algorithm.
In order to reduce the occurrence of subharmonic errors, YIN employes a cumulative mean function (equation 3.6) which de-emphasizes higher period dips in the difference function:

$$cmdf_t(\tau) = \begin{cases} 1, & \text{if } \tau = 0 \\ \frac{d_t(\tau)}{\frac{1}{\tau}\sum\limits_{j=1}^{\tau} d_t(j)}, & otherwise \end{cases} \tag{3.6}$$

Other improvements for the YIN f0 estimation system include a parabolic interpolation of the local minima, which has the effect of reducing the errors when the period estimation is not a factor of the window length used. (For a more complete discussion of this method, including computational implementation and results, see the cited paper)

3.2.3 The Combined Difference Function algorithm

Liu, Zheng, Deng and Wu proposed a new approach in order to calculate efficiently the Difference Function (equation 3.4) as an improvement of YIN method, using the FFT algorithm [3]. They calculated the Difference Function as the combination of two others kind of functions: the bidirectional and the circular difference functions. This two new functions are summed with a bias factor.

Bidirectional SMDSF

This function is calculated between two adjacent frames for two times: the first time from left to right and second one from right to left. The Bidirectional function is formed as the mean of the two new functions.

Left-To-Right

We expanded the difference equation $d_t(\tau)$, which is like the power of a binomial $(x+y)^2$, in the sum of its component :

$$d_t(\tau) = \sum_{j=t}^{t+N-1} x^2(j) + \sum_{j=t}^{t+N-1} x^2(j+\tau) - 2 \cdot \sum_{j=t}^{t+N-1} x(j)x(j+\tau) \tag{3.7}$$

In order to simplify the equation, one frame of the audio signal at time index t can be also defined as:

$$x_t(j) = \begin{cases} x(t+j), & j = 0, 1, \ldots, N-1 \\ 0, & otherwise \end{cases} \tag{3.8}$$

According to the last equation, we can transform the expanded difference function (equation 3.7) in a new simpler function:

$$d_t(\tau) = a_t(0) + r_t(\tau) - 2(a_t(\tau) + c_t(\tau)) \tag{3.9}$$

We now explain how to calculate the single components:

- $a_t(\tau)$: the equation 3.10 shows the autocorrelation function of the frame at the time index t (x_t).

  $$a_t(\tau) = \sum_{j=0}^{N-1} x_t(j)x_t(j+\tau) \tag{3.10}$$

  The equation 3.10 can be calculated efficiently and in a fast way by means of the FFT algorithm.

  $$X_t(f) = FFT(x_t) \tag{3.11}$$
  $$S(f) = X_t(f)X_t(f)^* \tag{3.12}$$
  $$a_t(\tau) = IFFT(S(f)) \tag{3.13}$$

  where x_t represents the frame at time index t; FFT is the Fast Fourier Transform; X_f is the FFT of the frame; S_f is the product in frequency domain; $IFFT$ is the Inverse FFT and $a_t(\tau)$ is the autocorrelation function.

- $r_t(\tau)$: the equation 3.14 represents is the frame's power at current lag τ, which is a recursive formula over τ in linear time.

$$r_t(\tau) = \begin{cases} a_t(0), \tau = 0 \\ r_t(\tau - 1) - (x(t + \tau - 1))^2 + (x(t + N + \tau - 1))^2, oth. \end{cases} \tag{3.14}$$

- $c_t(\tau)$: in equation 3.12 we see the cross-correlation between the two adjacent frames.

$$c_t(\tau) = \sum_{j=0}^{N-1} x_t(j + N - \tau) x_{t+N}(j) \tag{3.15}$$

  The equation 3.15 can be calculated efficiently by means of the following equations:

$$X_t(f) = FFT(x_t) \tag{3.16}$$

$$X_{t+N}(f) = FFT(x_{t+N}) \tag{3.17}$$

$$S(f) = X_t(f) X_{t+N}(f)^* \tag{3.18}$$

$$c_t(\tau) = IFFT(S(f)) \tag{3.19}$$

We finally have re-written equation (3.4) in a more efficient way in order to take advantage of the FFT algorithm and its low complexity. We obtain a final computational complexity of *O(Nlog$_2$N)*, much smaller than the starting *O(N^2)*. We refer to this this function as the **left-to-right SMDSF**.

Right-To-Left
In a similar way we can define a **right-to-left SMDSF** as:

$$d'_t(\tau) = \sum_{j=t}^{t+N-1} (x(j + N) - x(j + N - \tau)^2 \tag{3.20}$$

As we did before, we can expand the last equation in the following:

$$d'_t(\tau) = a_{t+N}(0) + r'_t(\tau) - 2(a_{t+N}(\tau) + c_t(\tau)) \tag{3.21}$$

The single components are:

- $\mathbf{a}_{t+N}(\tau)$: it's calculated as in equation 3.10.

- $\mathbf{c}_t(\tau)$: can be calculated with equation 3.15.

- $\mathbf{r}_t(\tau)$: is similar to equation 3.14 but is defined as:

$$r'_t(\tau) = \begin{cases} a_{t+N}(0), \tau = 0 \\ r'_t(\tau - 1) - (x(t + 2N - \tau))^2 + (x(t + N + \tau))^2, oth. \end{cases} \tag{3.22}$$

Also in this case we take advantage of the low time complexity of the FFT algorithm. This two equation (3.9 and 3.14) are the different functions at

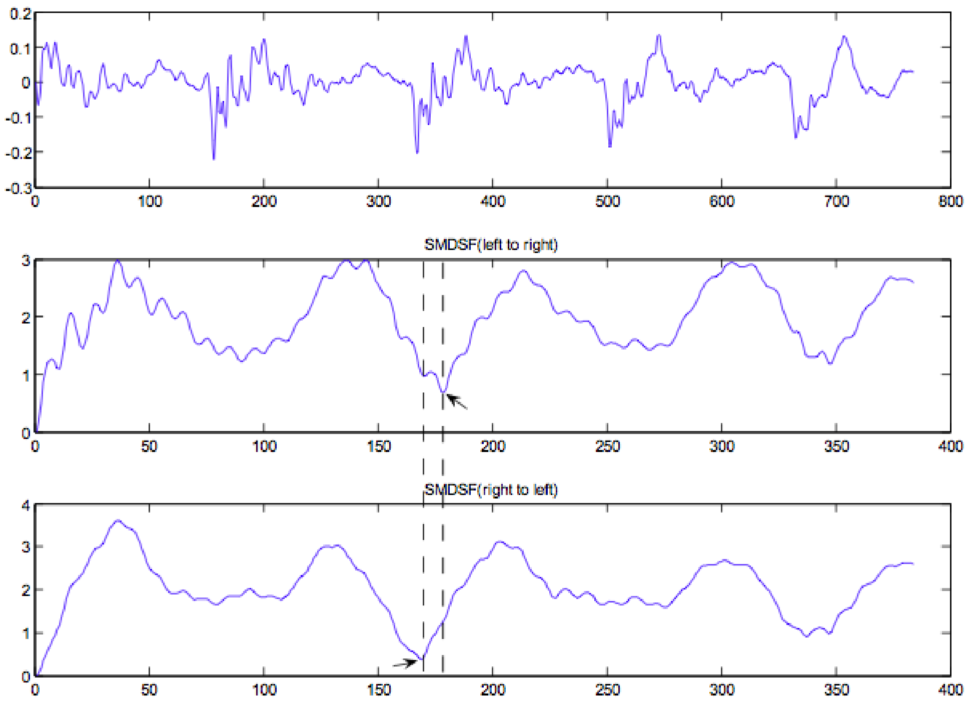


Figure 3.4: The difference between left-to-right SMDSF and right-to-left SMDSF

time index t and, considering that they may introduce some errors, we can define a **bidirectional SMDSF** as:

$$D_t(\tau) = \frac{d_t(\tau) + d'_t(\tau))}{2} \tag{3.23}$$

From this equation we can now estimate the pitch value of the frame at time index t+N

$$p(t + N) = \underset{p_{min} \leqslant \tau \leqslant p_{max}}{\operatorname{argmax}} D_t(\tau) \tag{3.24}$$

where p_{min} and p_{max} are the possible minimum and maximum pitch values respectively for a bass instrument. We setup this value accordingly to the lowest note for a common 4 string bass which is 41 Hz and the maximum one which is about 600Hz. As we can see in Table 3.1, pitch estimation using bidirectional SMDSF can lead to an average pitch value during two adjacent frames. In this way we can lower the doubling/halving error rate: the doubling error is when we retrieve a note one octave higher then its actual octave, the halving error occurs when the note retrieved is one octave lower its actual octave.

Method	Doubling (%)	Halving (%)
Left-to-right	5.8	1.5
Right-to-left	6.9	5.5
Bidirectional	**4.9**	**1.7**

Table 3.1: Doubling/halving error rates for the LR, the RL and the Bidirectional difference function

Circular SMDSF

We introduce now another method with higher halving errors, because we think that by combining it with the previous method, we can obtain a more balanced error level, with lower doubling and halving errors. A new type of SMDSF for this purpose is defined as:

$$D'_t(\tau) = \sum_{j=t}^{t+2N-1} (x(j) - x(t + (j + \tau - t)\%(2N)))^2 \qquad (3.25)$$

where "%" represents the modulo operation.
This function is called **circular SMDSF** due to the modulo operation on the sample point index. The analyzing frame size used in the circular SMDSF is $2N$, so we need two times the frame size used in the bidirectional SMDSF. This equation can be re-written with the help of the equation (3.10):

$$D'_t(\tau) = 2a'_t(0) + 2(a'_t(\tau) - a'_t(2N - \tau)) \qquad (3.26)$$

with the remind that the frame size is now $2N$ and not N. The computational complexity for the calculation of the circular SMDSF is still O(N log2(N)). The pitch value estimation is similar to that using the bidirectional SMDSF and the same equation (3.17) can be applied to estimate the pitch at time index t+N.
As we can see in Figure 3.5 the circular SMDSF is slightly different from the bidirectional SMDSF.

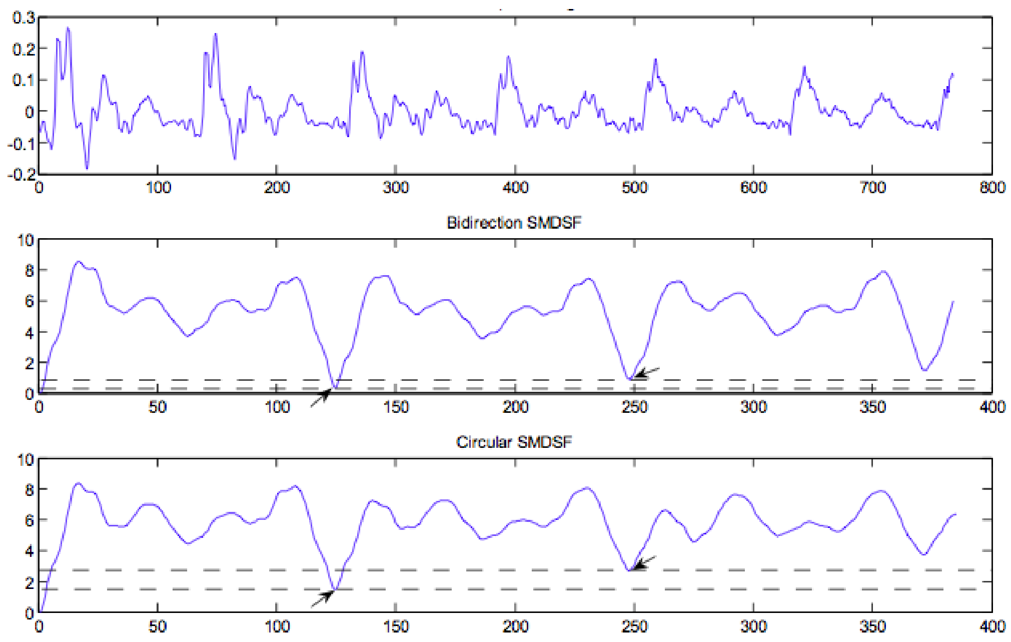


Figure 3.5: *The difference between the bidirectional SMDSF and the circular SMDSF*

Combined SMDSF

The bidirectional and the circular SMDSFs have their own characteristics, which are different in the doubling error rate and the halving error rate. This two functions can complement each other in some sense when they are combined together. A combined SMDSF is defined as a linear interpolation between the bidirectional SMDSF and the circular SMDSF:

$$D''_t(\tau) = \alpha D_t(\tau) + (1 - \alpha) D'_t(\tau) \tag{3.27}$$

Table 3.1 shows the error rates (with $\alpha = 0.3$) for the two method and for the final one, confirming our hypothesis: the bidirectional SMDSF has higher doubling error rate and the circular SSDMF has higher halving error rate, while the combined SMDSF has the lowest error and balanced doubling/halving error rates.

3.2.4 Cumulative Mean Normalized DF

This difference function is zero at the zero lag and often non-zero at the period lag because of imperfect periodicity. Unless a lower limit is set on the search range, the algorithm must choose the zero-lag instead of the period

Method	Doubling(%)	Halving (%)
Bidirectional	4.9	1.7
Circular	1.9	2.6
Combined	**2.0**	**2.1**

Table 3.2: Doubling/halving error rates using the bidirectional function, the circular function and the combined solution

one and the method should fail. The YIN algorithm introduce a solution to this problem with a normalization function. The solution is to replace the (combined) difference function with the Cumulative Mean Normalized Difference Function (CMNDF):

$$D''_t(\tau) = \begin{cases} 1, & if \tau = 0 \\ \frac{D''_t(\tau)}{(1/\tau)\sum\limits_{j=1}^{\tau} D''_t(j)}, & otherwise \end{cases} \tag{3.28}$$

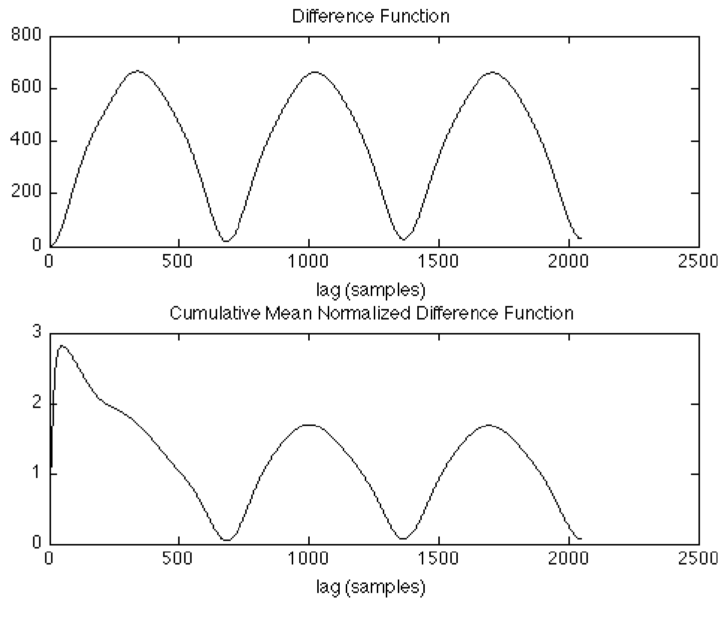


Figure 3.6: The difference between the DF and the CMNDF

The new function is obtained by dividing each value by its average over shorter-lag values. It differs from the combined difference function in that it starts at 1 rather than 0, tends to remain large at low lags, and drops below 1 only where the difference function falls below average. This solution reduces ”too high” errors and prevents high frequency contents and normalizes the function for the next steps.

3.2.5 Errors

Sampling, windowing and strong harmonic content are known to be the key factors that limit the accuracy of pitch estimation. Two typical kinds of errors in pitch estimation are period-doubling and period-halving. Many pitch estimation algorithms have methods to prevent these two types of errors from taking place. These methods generally consist of two stages: a pre-processing stage, using, for example, low-pass filtering and a post-processing stage. However, only one certain type of time-domain functions (ACF, AMDF, et c.) is used in these algorithms during pitch candidate generation, which inevitably limits the accuracy of pitch estimation. Different time-domain functions used in pitch estimation lead to different error distributions: some functions have a higher doubling error rate while others have a higher halving error rate. In our case a combined function is used, which has the common merit of several existing difference functions and it is shown to have the lowest error rate for pitch estimation.

3.3 MIDI

MIDI (Musical Instrument Digital Interface) is a standard protocol defined in 1982 that enables electronic musical instruments (synthesizers, drum machines), computers and other electronic equipment (MIDI controllers, sound cards, . . .) to communicate and synchronize with each other. MIDI does not transmit audio signals but it sends event messages about pitch, intensity and control signals for parameters such as volume, vibrato and panning, cues, and clock signals to set the tempo. The standard MIDI 1.0 specification permits to interpret any given MIDI message in the same way, and so all MIDI instrument can communicate and understand each other.
MIDI allows to store music as instructions rather than recorded audio waveforms and the resulting size of the files is quite small by comparison.
When a musical performance is played on a MIDI instrument, it transmits MIDI channel messages from its MIDI Out connector. A typical MIDI channel message sequence corresponding to a key being struck and released on a keyboard includes the pitch (expressed in value between 0 and 127), the velocity (which is the volume of the note, again between 0 and 127), a Note-On and Note-Off message. Other messages can be sent as well, like a program

change, aftertouch, pitch-bend messages.
In our work, the operating system itself associate sounds of the default wavetable to the MIDI musical messages. The wavetable sounds are, usually, those provided by the General MIDI (GM). GM includes a set of 120 standard sounds, plus drum kit definitions. All MIDI instruments and soundcards use the GM sound-set to ensure compatibility.

Chapter 4

System Design

This chapter illustrates the design phase of our system. The goal of this part is to properly chose and validate algorithms. In addition, the algorithm parameters needs to be set up to verify that the results agree with our initial expectations. As a result of this phase a prototype has been built and used as a test for the next implementation step. Thanks to the easy of use, the great amount of available functions and the aptitude to work with digital signals we chose to use the Matlab framework to create the prototype.
After a first introduction on the environment and the tools used, we present the algorithm implementation details

4.1 Tools and Frameworks

In this section we illustrate the framework used and the tools that helped us to realize the prototype.

4.1.1 Matlab [1]

The prototype has been created within the Matlab framework because of the easiness of its use with mathematical functions and digital signal processing. Matlab is a high-level language which provides the user many functions ready to use. It is an environment that provides good support for mathematical operations, for example, about array operations as well as with signal processing. It permits us to perform fast calculation and can gives a real-time feedback of our results. Matlab let us to write algorithms in a easy way, with few source code lines, and in a performing way. It helps a lot with an easy debug interface, and the possibility to visualize quickly

[1]Matlab, http://www.mathworks.com/products/matlab

the data. By these fact we chose Matlab to design and test the prototype. Moreover, Matlab has the possibility to add some external plug-in to extend the environment. We used the PlayRec utility for the audio management, and the MIDI Toolbox for notes creation and visualization.

4.1.2 PlayRec [2]

Since one of the main requirements of our system a real-time feedback to the user and since Matlab doesn't integrate any native toolbox for real-time audio recording and playback, we used Playrec, that is an external plug-in. Playrec is a Matlab utility that provides simple and versatile access to the sound-card using PortAudio, a free, open-source audio I/O library. It is multi-platforms and provides access to the sound-card via different host API. It offers a non-blocking access to the sound-card: all samples are buffered so Matlab can continue with other processing while output and recording occur. New output samples are automatically appended to the remaining samples: this makes it possible for the audio data to be generated as required. The only limit for PlayRec is the processing power of the computer: lower computational power means higher latency, sample skipping, glitches and delays.
Before any kind of audio is played or recorded, PlayRec must be initialized: the audio device and the frequency sampling must be defined. PlayRec divides the signal in frames called "pages" with a sample-rate depending length: the set up of the pages is peculiar to avoid clicks, glitches, delay or pause whilst playing or recording. Pages are then sequentially collected in a buffer, from which it's possible to extract data needed for our operations.

4.1.3 MIDI Toolbox [3]

Since one purpose of the system is to show the notation of the transcribed song, we used an external plug-in to translate the result of the analysis step to a human-readable form, as standard notation. The MIDI Toolbox is a compilation of functions for analyzing and creating MIDI files in Matlab environment. It also offers the possibility to show a notation of the MIDI file created. The toolbox supports the creation of MIDI messages with note pitch, timing and velocity information that MIDI provides.

[2]PlayRec, http://www.playrec.co.uk

[3]MIDI Toolbox, https://www.jyu.fi/hum/laitokset/musiikki/en/research/coe/materials/miditoolbox

4.2 Implementation

The prototype performs a real-time transcription both from a loaded audio file and from a live input bass. By this fact, two different systems have been created, although the main analysis part is the same for both. In the following sections the systems differences are explained, while the similar blocks are described afterwards.

4.2.1 Audio file acquisition

In Figure 4.1 the overview of the system in the case of an input audio file is presented. In this case the audio input source is represented by an audio

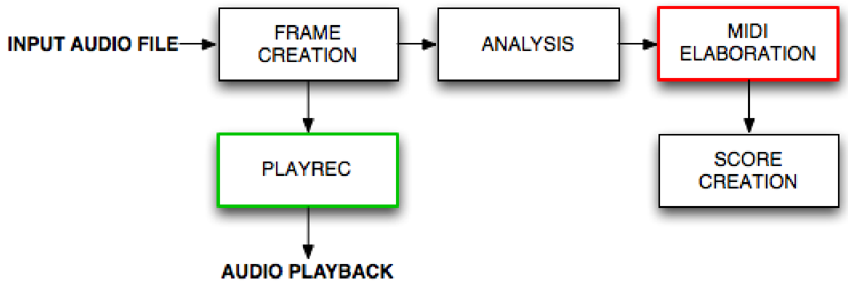


Figure 4.1: System overview for an audio file

file. As the audio file is already available, we don't need to use the Playrec utility for the acquisition, but, instead, it will be used for the playback. With the Matlab function

waveread(file_name, [start_Sample end_Sample])

we can read the audio file block by block, telling the function the first sample and the last sample to read. The size of each block (or frame) is set up to 2048 samples for the reason explained in chapter 3.
The PlayRec module has been used for playing the audio file. As frames are read, they are pushed in the Playrec output buffer:

playrec('play', Block To Play, Channel List)

Playrec manages the playing of the samples in the output buffer so as not to listen to glitches, pauses or delays. This is the main difference with respect to the real-time acquisition, which uses the Playrec utility also for the acquisition of the signal audio.

4.2.2 Real-time acquisition

As we said in the introduction, the application provides a real-time transcription also from real-time acquired data. This is possible in Matlab thanks to the PlayRec extension.
In figure 4.2 we can see the overview of this case.

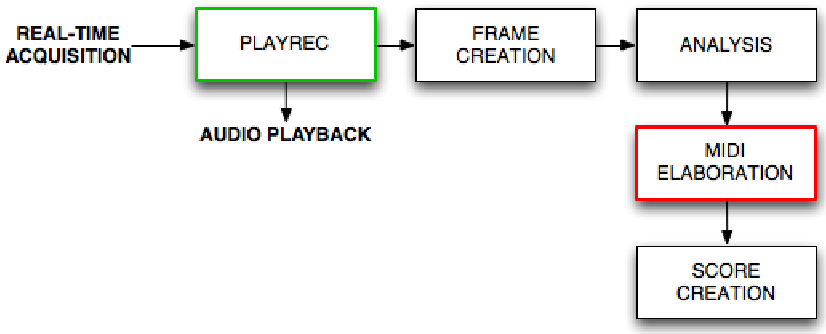


Figure 4.2: System overview with bass plugged-in

The main difference with the case of an input audio file is that the audio data is acquired in real-time.
Playrec provides support for reading data in real-time thanks to the division in pages explained before. With the following functions

page = playrec('playrec', Temp Page, PlayChannel, -1, RecChannel);
pageList = [pageList newPage];
playrec('getRec', pageList(1));

we create a new page containing both sample input (recording) and output (playing). This page is pushed in the Playrec page buffer and then the samples are retrieved from the first available page in the buffer. By means of this procedure, Playrec store the pages and use them as soon as they are available and the previous pages are used. It manages the playing in an autonomous way and the pages are played at the right moment.
We set the length of the page equals to 512 samples: in this way Playrec can continuously read, store and play the data without glitches and considerable latency. Each time the buffer reach 4 pages (=2048 samples) a new frame for the analysis is ready. As we can see in PlayRec functions we can set the number of channels to be recorded or played: in the case of monophonic audio the number of channel is always set to 1.

In the next sections we will explain the remaining blocks which are the same for both cases.

4.2.3 Frame creation

This section illustrates how the signal is fragmented from the input source. Both in the case of audio file and real-time acquisition we obtain a digital audio signal. This signal is divided in frames of 2048 samples length. By the algorithm explained in chapter 3, we know we need to collect two frames to start the processing. In Figure 4.3 we show the organization of the blocks.

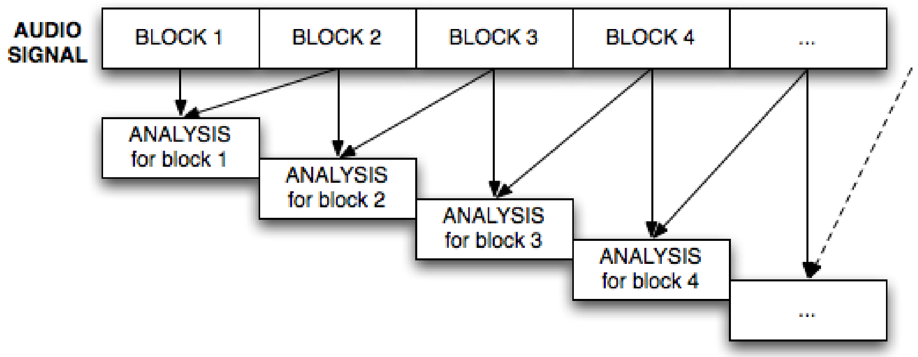


Figure 4.3: Blocks organization

We can see that the first two blocks contribute to the analysis of the first frame only. The second and third block for the second frame, and so on... This frames are processed as in the following analysis section.

4.2.4 Analysis

Once the audio signal has been acquired and segmented into frames, we can start the main processing of the prototype. If we zoom in on the analysis block in Figure 4.1(or 4.2) we obtain the scheme in Figure 4.4. This section illustrates an overview of the analysis.

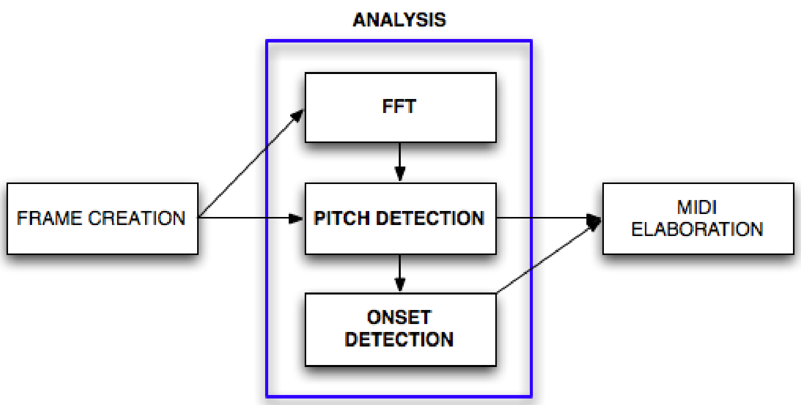


Figure 4.4: Analysis overview

The pitch detection stage need two adjacent frames to correctly retrieve the pitch. In Figure 4.5 we can see how frames are managed as input of pitch detection. Two adjacent frames are collected and their FFT is calculated; the frames and their spectra are the input parameters for the pitch estimation algorithm.

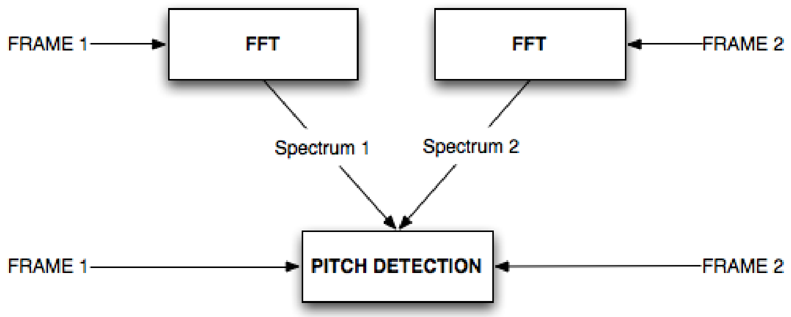


Figure 4.5: Blocks' structure of the pitch detection phase

The analysis section is composed by three main steps:

- FFT: it performs the Fourier transform of the input frame.
- Pitch Detection: from the input frame and the FFT frame, it returns the fundamental frequency value.
- Onset Detection: it returns the temporal instant of the beginning of the note.

Both pitch detection and onset detection blocks provide informations for creating the notes and the score.
In the following sections we describe each block.

FFT

An extensive use of the Fast Fourier Transform (FFT) is done. FFT is an efficient algorithm to compute the Discrete Fourier Transform (DFT) and its inverse. A DFT permits to investigate the frequency characteristics of a signal. It is useful to analyze the frequencies contained in a sampled signal. The DFT is a computationally very onerous operation. An FFT is a way to compute the same result more quickly: computing a DFT of N points using the definition, takes O(N2) arithmetical operations, while an FFT can compute the same result in only O(N log N) operations. The difference in speed is substantial, this is the reason because it's widely used in digital signal processing.
Matlab provides a fast implementation of the FFT: their algorithm is based on FFTW, "The Fastest Fourier Transform in the West" [4].
The Matlab command

$$blockFFT = \textit{fft(block, size(block))}$$

has been used to calculate the transform of the frame. The size indicate the transform length: the number of samples on which the FFT should be calculated.
For each frame of the audio signal the FFT is computed on 2048 samples (the frame length): the frequency bin is wide

$$\frac{Fs}{N} = \frac{44100}{2048} = 21Hz \tag{4.1}$$

[4] FFTW, http://www.fftw.org

PITCH DETECTION

The pitch estimation step is performed using YIN [4] and Combined Different Function [3] algorithm.
As we collect two adjacent frames and their FFT, the correlation between them it's explored by means of the Combined Difference Function, as explained in chapter 3. Then, the fundamental frequency can be estimated and a residual of the difference function is used to build the onset function.
In Figure 4.6 the pitch detection model is presented and in the following sections we explain all the elements.

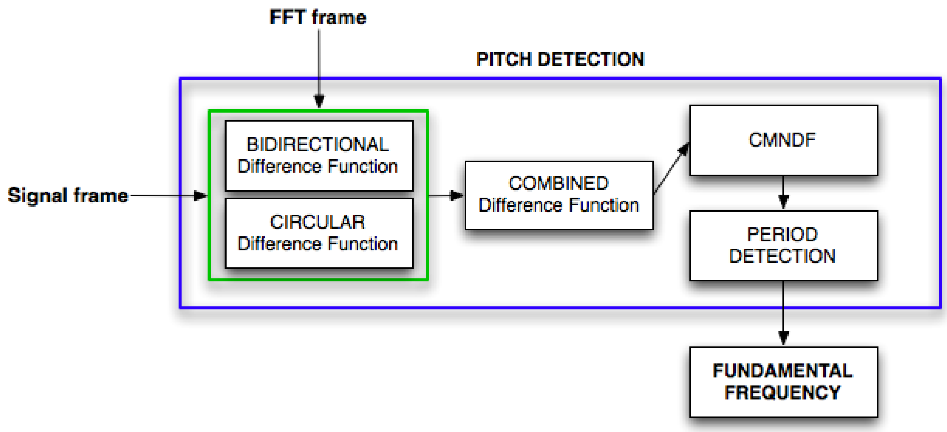

FFT frame
PITCH DETECTION
Signal frame
BIDIRECTIONAL Difference Function
CIRCULAR Difference Function
COMBINED Difference Function
CMNDF
PERIOD DETECTION
FUNDAMENTAL FREQUENCY

Figure 4.6: Pitch Detection structure

Bidirectional Difference Function As we know by the Combined Difference Function algorithm (chapter 3, equation 3.7) we need to calculate the difference function of the two collected frames. The Left-To-Right (equation 4.2) and Right-To-Left (equation 4.3) Difference Function are first computed:

$$d_t(\tau) = a_t(0) + r_t(\tau) - 2(a_t(\tau) + c_t(\tau)) \tag{4.2}$$

$$d'_t(\tau) = a_{t+N}(0) + r'_t(\tau) - 2(a_{t+N}(\tau) + c_t(\tau)) \tag{4.3}$$

In both equations components are, a_t the autocorrelation of the frame, r_t the power of the frame and c_t the cross-correlation between the two frames: these are typical functions in digital signal processing and can be efficiently calculated by means of the FFT Matlab function (as explained in Chapter 3).

The Bidirectional Function is formed as the mean of two different functions:

$$D_t(\tau) = \frac{d_t(\tau) + d'_t(\tau))}{2} \tag{4.4}$$

Circular Difference Function Also in this case we take advantage of the low time complexity of the FFT function to calculate the Circular Difference Function. The two adjacent frames are joint forming a new frame of length *2*2048 = 4096* samples. The different function is calculated on this new longer frame:

$$D'_t(\tau) = 2a'_t(0) + 2(a'_t(\tau) - a'_t(2N - \tau)) \tag{4.5}$$

where N = 2048 and a'_t is the autocorrelation.

Combined Difference Function Once the Bidirectional and the Circular DF are computed, we form the Combined DF by means of the following formula:

$$df = \alpha * D'(\tau) + (1 - \alpha) * D''(\tau) \tag{4.6}$$

In figure (fig. 4.6) we can see an example of a Combined DF of a frame.

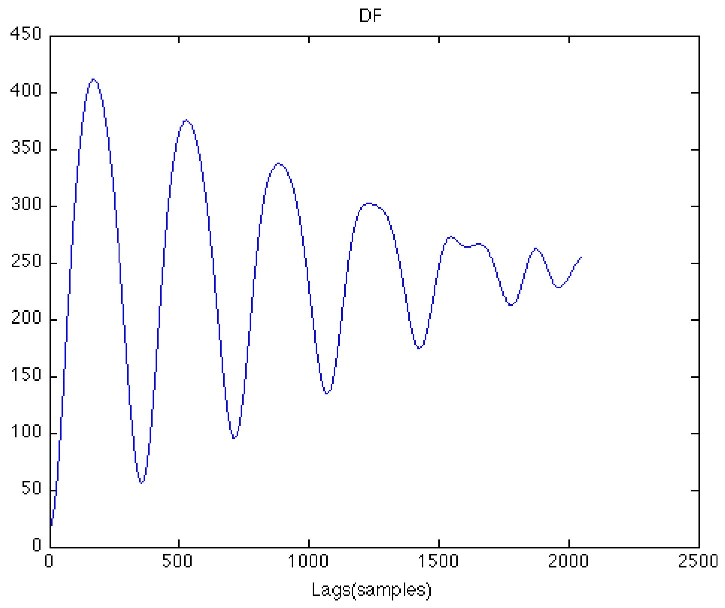


Figure 4.7: Combined DF of a frame

The tuning of the α parameter is critical for the correct algorithm working. The value $\alpha = 0.35$ is found experimentally, testing the prototype with several audio files.

Cumulative Mean Normalized Difference Function We now use the procedure explained in the YIN algorithm (chapter 3, section 2.4) to normalize the Combined Difference Function.
With the Cumulative Mean Normalized Difference Function (CMNDF), the output of the Combined Difference Function is then normalized. Experimental results show that the CMNDF has more stable estimation values than the original function. We can see that the function starts now from the 1 value, while in the Combined DF at zero lag we also have the lowest value compromising the correct research of the fundamental period.
In Figure 4.8 an example of a CMNDF of a frame is presented.

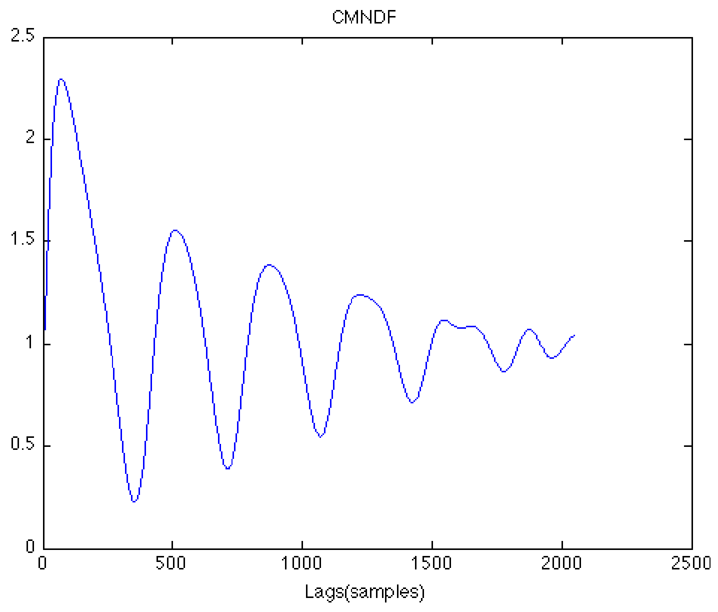


Figure 4.8: CMNDF of a frame

At this point we obtained the function needed for the fundamental period estimation. This function (an example is shown in Fig. 4.8) is calculated for each frame in order to extract the relative F0 value.

Fundamental Period Detection

From the CMNDF function (see Section 4.2.4) we can retrieve the fundamental period of the current frame. We search for the first minimum below a threshold k. The location of this minimum (lag τ) gives us the fundamental period of the frame. If none minimum below the threshold is found, we chose the location of the global minimum. From the location (τ) we can easily determine the frequency:

$$T = \frac{\tau}{Fs} \tag{4.7}$$

$$F0 = \frac{1}{T} \tag{4.8}$$

where T is the period, τ is the lag and F0 is the fundamental frequency of the frame.
The value of the threshold k has been found experimentally.
In listing 4.1 the script for the period detection is shown.
As how we created the pitch detector, it returns also the value of the lag at the selected period position. This value is collected frame by frame to form an onset detection function.

Listing 4.1: Period detection Matlab script

```
% Search for values smaller than threshold k
threshold = find( cmndf < k);
if ( isempty(threshold) )
  % if we haven't any value < k
  % than take the smallest lag
  [value(1) period(1)] = min(cmndf);
else
  % else take the smallest lag
  % which value is smaller than k
  [value(1) period(1)] = min(threshold);
end
% convert the lag value in frequency
f = period/Fs;
f = 1/f;
```

ONSET DETECTION

The detection of the fundamental period gives us also, the relative value of the chosen lag and we called it the onset value. We retrieve one onset value for each frame and this value is used frame-by-frame to investigate about the note onset. If we could collect this values an onset function as the one represented in Figure 4.9 could be obtained.

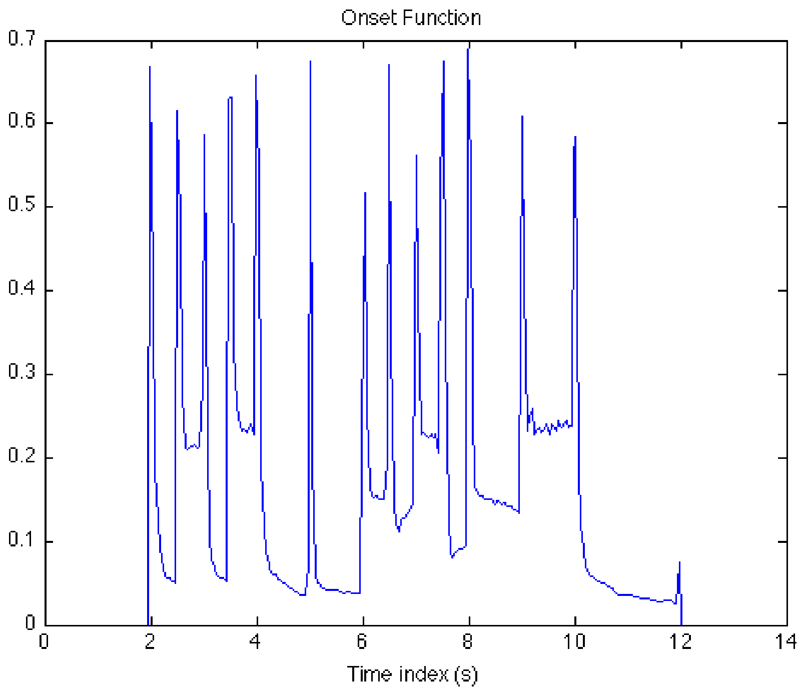


Figure 4.9: Onset Detection Function

By this new function we can easily find the notes onset, offset and their length.
The problem is that in real-time we do not have the complete function, but just the current and the previous onset values. We need to perform a real-time peak picking algorithm to isolate the peaks, which represents the starting time of the notes, from the valleys. By means of an absolute threshold, experimentally retrieved, and performing a comparison between the current onset value and the past three values we can determine if the current onset value represents the starting time of the note. In the following code, the real-time peak picking algorithm is shown.

Listing 4.2: Onset Detection Function

```
i = 4;
k = i-1;
difference = onset(i) - onset(i-1);

if (onset(i) > onset(i-k:k))
    if onset(i) > 0.3
        if difference > 0.1
            temp = find(on(i-k:k) == 1);
            if numel(temp) > 0
                if onset(i) > onset(i-temp)
                    on(i) = 1;
                    cont_block;
                    temp;
                    on(i+(temp-4)) = 0;
                else
                    on(i) = 0;
                end
            else
                if cont_block - pos > 4
                    on(i) = 1;
                    pos = cont_block;
                else
                    on(i) = 0;
                end
            end
        else
            on(i) = 0;
        end
    else
        on(i) = 0;
    end
else
    on(i) = 0;
end
```

With this algorithm is as if we create a new onset function with peaks only. In Figure 4.10 we can see the new onset function.

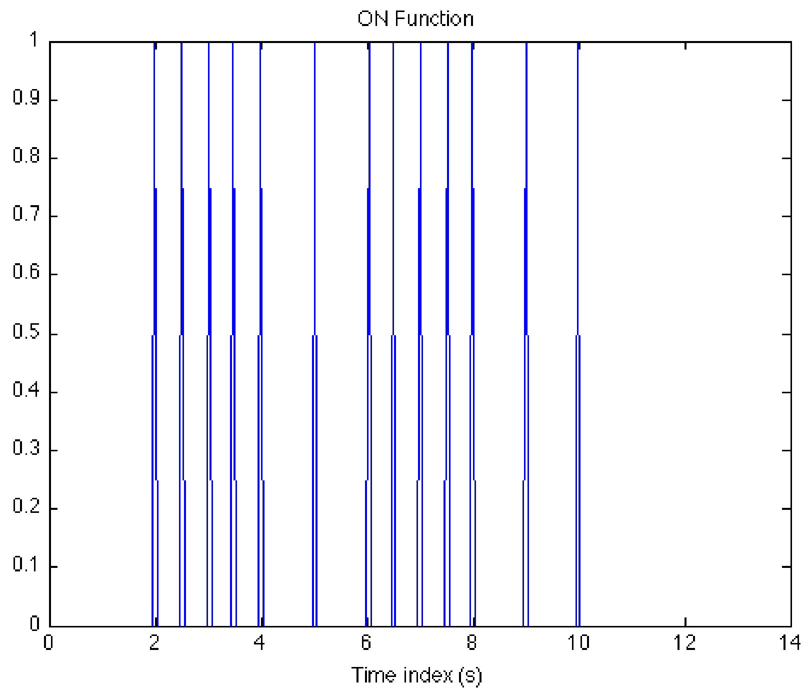


Figure 4.10: The new Onset Detection Function

4.2.5 MIDI Elaboration

Once we obtained the fundamental frequency and the note starting instant we need to create the corresponding note object and visualize it. As said previously we have chosen MIDI messages as a representation. The MIDI toolbox helps us realizing this.

Before, we need to convert the F0 into the relative MIDI note number. MIDI note notation is one of several methods that name the notes of the standard Western chromatic scale by combining a letter-name, accidentals, and a number identifying the pitch's octave (like A2, C4, E3, etc...). C0 is in the region of the lowest possible audible frequency at about 16 Hz. In this system, middle C (MIDI note number 60) is C4 and the MIDI note number 69 (A4 = 440Hz) is used for tuning and for calculating the other note numbers. By means of the following formula we can convert the F0 value to the corresponding MIDI note number :

$$midi = round(69 + 12 * log2(f/440)); \tag{4.9}$$

Where f is the fundamental frequency and 440 Hz is the reference value for the note A above middle C (C4).

With the MIDI note number and length we can create an array for each note:

row = [onset(beats); duration(beats); midi_channel; pitch, velocity=120; onset(s); duration(s)];
midi_matrix(contatore_note, :) = row;

In the row array we have the onset and the duration both in beats and in seconds, the midi channel to use, the velocity and pitch which is the transformed frequency we retrieved. Pushing each row in a matrix (midi_matrix) we obtain a score matrix to be used with the MIDI Toolbox in order to create the score and the MIDI file.

4.2.6 Score Creation

With the help of the MIDI toolbox we created a midi matrix in which every row is a MIDI note with its pitch and duration. The MIDI Toolbox provides a set of functions for visualizing a notation of a MIDI file: it offers a pianoroll notation. Pianoroll is a simple representation of piano notes with a time axis.
The notation is performed in real-time: as the algorithm find a note, it appears immediately in the notation. With a call to the function

pianoroll(midi_matrix);

the pianoroll visualization is created as in Figure 4.11. The horizontal line represents the reference C3 note.

4.3 Conclusions

The system has been tested both with audio files and realt-time bass. Encouraging results were obtained from these test. The main problem has been with the real-time performances: long latency has been experienced. This may me caused by the Matlab inability to work with real-time processing or by the total low computational power as the sum of the system, Matlab, Playrec and script realized.
In the next implementation step this problem will be solved.

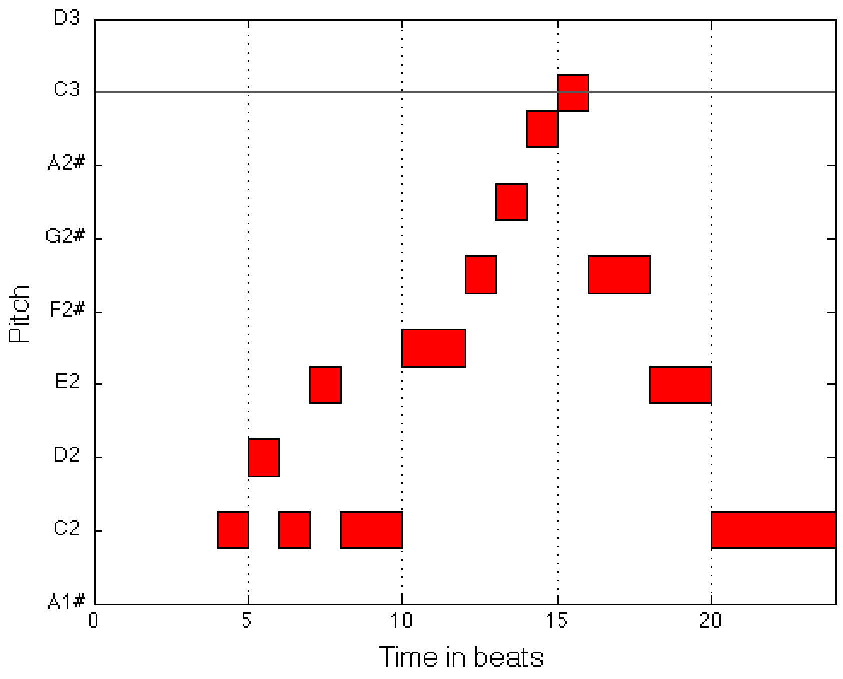


Figure 4.11: Piano roll visualization

Chapter 5

Software development

In the previous chapter we illustrated the design of the application's prototype. The algorithm has been tested and the parameters have been set up. In this chapter we focused on the development details of the software application realized.

5.1 Requirements

Let's imagine a new user approaching at this application for the very first time. He would like to understand its usage almost immediately. He may wants to try it first with a recorded bass line. So he runs the application and loads an audio file: if everything works, he could decide to to plug the bass directly in the computer. Probably he would like to listen at what he's playing, and it would also be nice to record his performance and make it available for playing/editing. And the score and the midi file accessible as soon as possible.
If we think at this typical scenario we can get some important information about the requirements to meet:

- Application usability: we need to realize a simple and friendly interface for a variety of users, from the professional musician to the entry-level music student to the amateur. The graphical interface should then be accurate, simple to understand and clean.

- Input: the application need to transcribe a music excerpt both from audio files and from real-time performances.

- Fast computation: the computation part should be pretty fast and accurate in order to have a real-time feedback. We need a fast and reliable environment to work on.

- Audio playback: the user wants to hear back at what is listening. This part should be seriously taken in account. Not everybody has a bass amplifier or a professional sound card for recording and this could be a point worthy of remark.
- Metronome: playing with a metronome is very important for a musician. We should give the user the possibility to use it.
- Score: the score is the most important feedback for the user. It would be nice for him to modify some notes or adding others and listen back to the changes.
- Midi/MusicXML: we can give the user the possibility to export the midi and music xml file for future editing.

5.2 Environment and libraries

To meet the requirements and offer to each potential user the possibility to use the application, we chose a platform-independent programming language: Java. With Java, we can also solve the latency problems in the real-time processing occurred in the prototype implementation. In this section we present the environment and the libraries used.

5.2.1 Java [1]

Java is a programming language introduced in 1991 and now it runs on more than 850 million personal computers worldwide, and on billions of devices worldwide, including mobile and TV devices. This is one reason to develop the application with Java: we are sure it will works on many computers with a little effort. In fact, Java applications are compiled to bytecode that can run on any Java Virtual Machine (JVM) regardless of computer architecture. Further more, there are a lot of libraries that can be added to extend the environment. Among all libraries we used JTransform, Java Sound, JMusic and JFreeChart. The first let us calculate efficiently the FFT transform. Java Sound us manage the audio playback and recording at a low-level programming. JMusic help us to create the score view of the transcribed work. The last library is useful for plotting graphs.

[1]Java, http://www.java.com

5.2.2 JTransform [2]

JTransforms is an open source FFT library written in Java. It permits the calculation of the Discrete Fourier Transform (DFT) by means of the Fast Fourier Transform (FFT). The code is derived from General Purpose FFT Package [3] written by Takuya Ooura and from Java FFTPack [4] written by Baoshe Zhang.

5.2.3 Java Sound [5]

The Java Sound API [17] specification provides low-level support for audio operations such as audio playback and capture (recording), mixing, MIDI sequencing, and MIDI synthesis in an extensible, flexible framework. It provides explicit control over the capabilities normally required for sound input and output. It represents the lowest level of sound support on the Java platform. For example, the Java Sound API supplies mechanisms for installing, accessing, and manipulating system resources such as audio mixers, MIDI synthesizers, other audio or MIDI devices, file readers and writers, and sound format converters. The Java Sound API does not include sophisticated sound editors or graphical tools, but it provides capabilities upon which such programs can be built.
Java Sound is composed by two main package: Sampled and MIDI. We used the Sampled package which provides interfaces and classes for capture, processing, and playback of sampled audio data. The MIDI package provides interfaces and classes for I/O, sequencing, and synthesis of MIDI data, and it was used for the metronome.

Java Sound Sampled

The package *javax.sound.sampled* is good for our purpose: it handles digital audio data, which the Java Sound API refers to as sampled audio. The Java Sound API does not assume a specific audio hardware configuration; it is designed to allow different sorts of audio components to be installed on a system and accessed by the specific API. The Java Sound API supports common functionality such as input and output from a sound card (for example, for recording and playback of sound files) as well as mixing of multiple streams of audio.

[2] JTransform, http://sites.google.com/site/piotrwendykier/software/jtransforms

[3] General Purpose FFT Package, http://www.kurims.kyoto-u.ac.jp/%7Eooura/fft.html

[4] Java FFTPack, http://jfftpack.sourceforge.net/

[5] Java Sound, http://www.oracle.com/technetwork/java/index-139508.html

A typical audio architecture is shown in Figure 5.1:

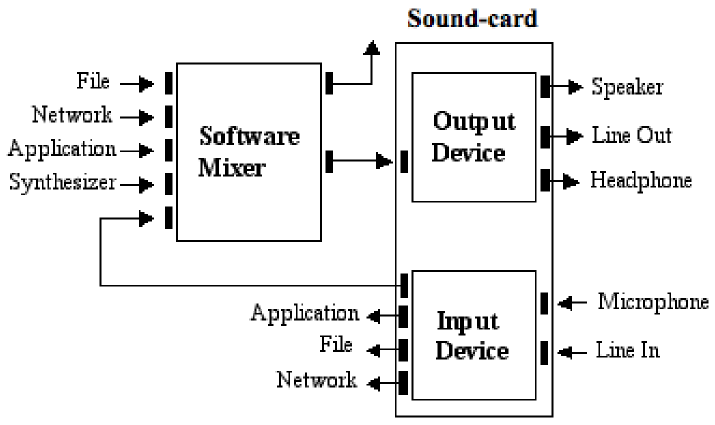


Figure 5.1: A typical audio architecture

A device such as a sound card has various input and output ports, and mixing is provided in the software. The mixer might receive data that has been read from a file, streamed from a network, generated on the fly by an application program, or produced by a MIDI synthesizer. The mixer combines all its audio inputs into a single stream, which can be sent to an output device for rendering. To play or capture sound in our application we need three different components:

- Formatted audio data: it refers to the audio format used. An audio format tells how to interpret a series of bytes of "raw" sampled audio data and tells you the sample rate and the number of bits per sample. In our case the PCM standard audio format has been used. The audio format we used accounts for: 16 bit per sample, sampling rate of 44100 Hz and 1 channel for monophonic audio.

- Mixer: the purpose of a mixer is to handle one or more streams of audio input and one or more streams of audio output. It mixes together multiple incoming streams into one outgoing stream.

- Line: a line is an element of the digital audio "pipeline", that is, a path for moving audio into or out of the mixer. As metaphor, lines are analogous to the microphones and speakers connected to a mixing console.

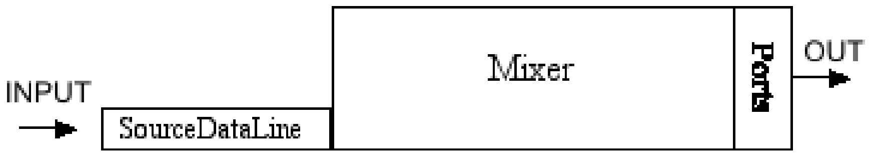


Figure 5.2: A line configuration for audio output

In Figure 5.2 an application has got access to some inputs of a mixer: a source data lines. A Source Data Line is a mixer input that accepts a real-time stream of audio data. The application pushes the audio data into the source data lines, a buffer at a time. The mixer reads data from the line, mixes the dry audio signal and delivers its final output to one or more output ports, such as a speaker or a headphone jack. The same can be done for an output line, called Target Data Line.

5.2.4 JMusic [6]

jMusic [18] is a library written for musicians in Java programming language. This library is simple enough for newbie programmers but sophisticated enough to enable composers to accomplish real work. It is an useful API for music software development. JMusic was basic for our application because it let us create the score, adding notes and obtain the visualization of the score notation.

5.2.5 JFreeChart [7]

JFreeChart is an open source library available for Java that allows to generate graphs and charts. It is particularly effective when it's needed to regenerate graphs that change on a frequent basis. The library has been used in the debug phase of the development of the application and to offer a real-time feedback. As jMusic library do not support a real-time visualization of the score, we plot a representation of the score in a format similar to the pianoroll.

[6] JMusic, http://jmusic.ci.qut.edu.au

[7] JFreeChart, http://www.jfree.org/jfreechart

5.3 Implementation

As explained in the requirements, the application performs music transcription both from file or from a plugged bass. For this reason we created two different Java classes to improve the performances in each case. The overall arrangement is the same: in the next sections we will explain the differences between the two classes.
An overview of the application structure is given in Figure 5.3.

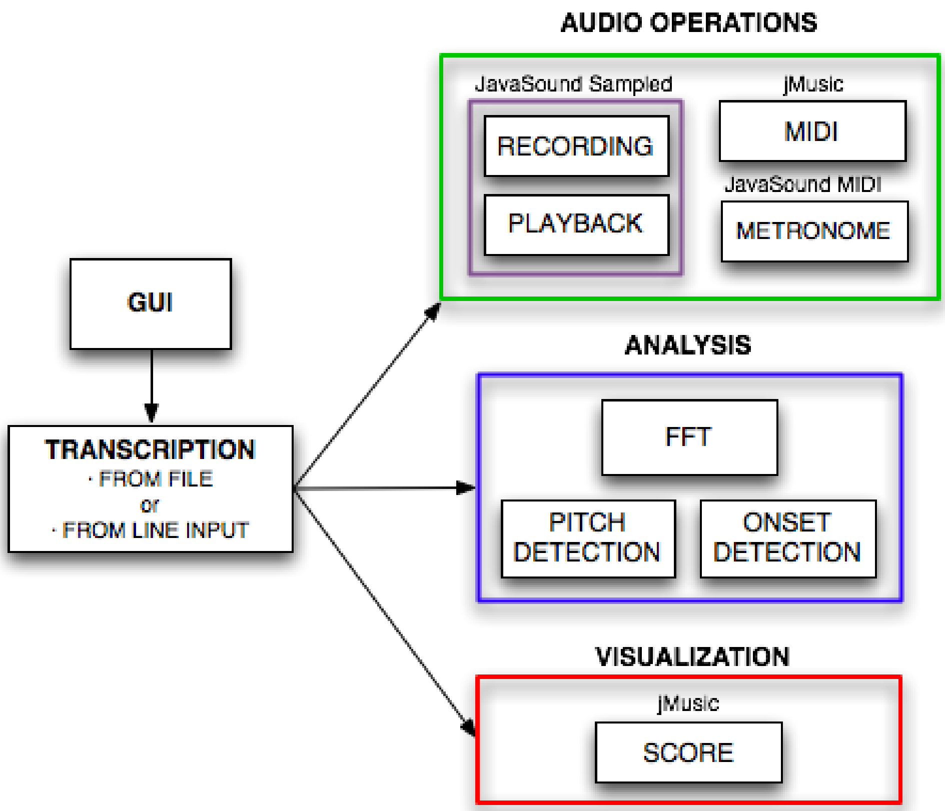


Figure 5.3: Logic scheme of the Java application

- GUI: it refers to the user interface. It goes between the user actions and the application reactions. To the GUI belongs buttons, textfields and other component for the application control.
- Transcription source: through the GUI the user decide what to transcribe, if a recorded song or a bass from the input line. This informa-

tion is essential for the setup of the relative classes.

- Audio operations: it manages all operations such as audio data acquisition, audio playback, audio recording, midi creation, midi playing, metronome playing. This part is performed thanks to the Java Sound library. jMusic library is used for the Midi section.
- Analysis: this part includes the signal processing, the algorithm implementation, the midi conversion and the notes creation. For an in-depth examination we suggest to read chapter 4.
- Visualization: display the score and its graphical interface provided with the jMusic library. Furthermore, it manages the creation of a graph where a kind of piano-roll is represented.

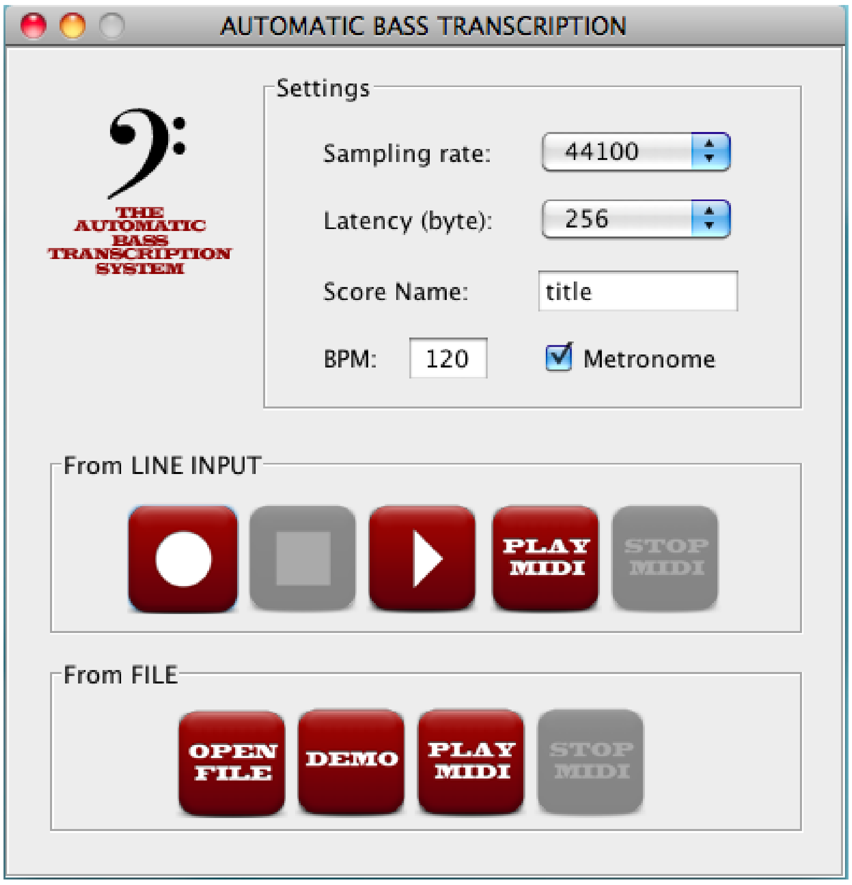
In the next sections all components are illustrated.

5.3.1 GUI

GUI stands for Graphical User Interface. It represents the tool that allows users to interact with the application. By requirements we tried to design it as simpler as possible, to be understand from the very first use. Few buttons are used and the overview is clear and simple.
In figure 5.4 we take a look of the interface: it is divided in three panels.

- Settings: The user can here set up some parameters used in case of a live performance. The sampling rate is set by default at 44100Hz. The latency value measure the block length to be read and sent to the output as explained up ahead (Section 5.3.3). The score name is needed for the score. While the timing (in bpm) set the duration of the notes and give the metronome (if activated) the right beat.
- From Line Input: This panel controls the application in the case of a live performance. When Rec button is clicked the application start recording and acquiring the input audio data, the analysis is performed, and the transcribed score is shown when the user click on the Stop button. After this operations the user can listen to his performance or play (and stop) the midi file just created.
- From File: If an external file is opened the transcription analysis starts immediately. Alternatively, an example audio file is pre-loaded in the application for demo purpose.

The GUI accounts also for the creation of the thread involved in the analysis and in the visualization process of the selected input.



Settings
Sampling rate: 44100
Latency (byte): 256
Score Name: title
BPM: 120
☑ Metronome

Figure 5.4: Application user interface

5.3.2 Thread

Since we wants to maximize the real-time experience, as shown in Fig. 5.3, the macro-blocks (Audio operations, Analysis, Visualization) are managed using different synchronized thread running in parallel.
A thread is a division of the process in two or more parts executed concurrently. The Java Virtual Machine allows an application to have multiple threads of execution running concurrently. Multithreaded applications deliver their potent power by running many threads concurrently within a single program. From a logical point of view, multithreading means multiple lines of a single program can be executed at the same time. By starting a thread an efficient path of execution is created while still sharing the original data area from the parent.
In the application we have three main part that runs concurrently: the GUI,

the I/O audio operations and the processing. Threads are used for audio playback and recording. In a separated thread we process the input signal. All threads are created by the parent class constructor and controlled by the GUI.

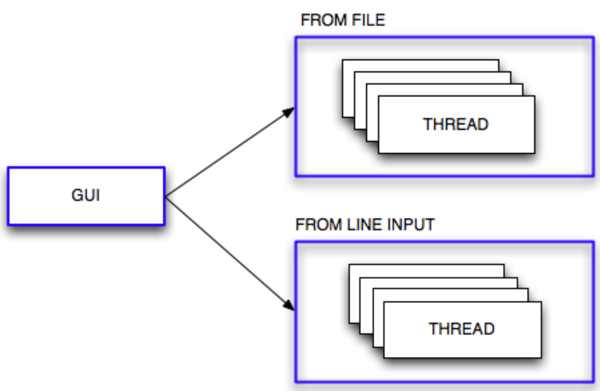


Figure 5.5: Use of thread in the application

5.3.3 Analysis

In this section we will focus on the real-time modality of the processing. The other blocks of the analysis section are the Java transposition of the one realized in Matlab (see Chapter 4).
The attention now is on the audio data acquisition process.
Java Sound let us acquire data in real-time from the input stream. Once the input and output lines are correctly opened and started, the audio stream flows in the buffer. For bring latency down we need to read small frames at a time, send them to the output buffer and store them in a new buffer until the correct size is obtained. In this way, while acquiring new audio data, we can listen to it and begin the analysis only when the needed samples are collected. We set the length of the small frames to 128 samples in order to avoid latency. Anyway, this value can be modified by the user in the settings panel of the user interface.
Considering that a block is formed by 2048 samples, we need 8 small frames to form a block. The acquisition step and the analysis processing are performed in separated thread: this provides low latency level and a direct feedback for the user.
In Figure 5.6 we depict the arrangement of the data acquisition.
Blocks are created from smaller frames taken from the input stream. Frames

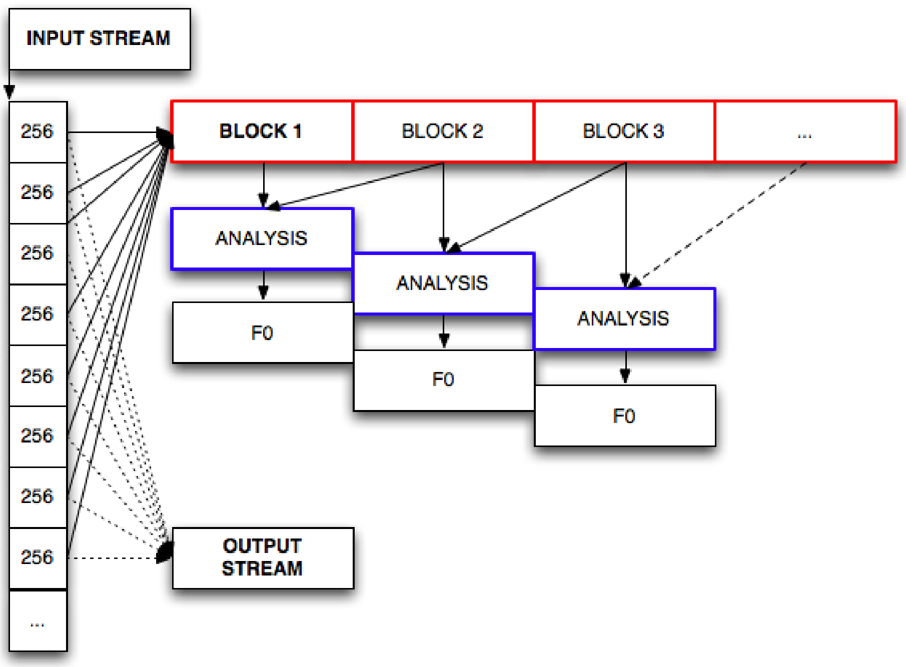


Figure 5.6: Audio blocks segmentation

are collected to form one block. As a block is created the process continue to form the other blocks. The analysis starts only when two consecutive blocks are collected: from the first two blocks we estimate the pitch of the first block. From the second and the third we estimate the pitch of the second block, and so on...
Obviously some part of the analysis, like the FFT transform (using JTransform), is reused in the next step. There is a variable recovery that speed up the algorithm execution time. The remaining process of the algorithm is much similar to the one in the Matlab development (see chapter 4): the FFT is performed and then pitch detection and onset detection are calculated in the same way.

5.3.4 Audio Operations

This section is about the audio data acquisition and operations.

Java Sound

We deals with the creation and the control of the mixer and the I/O lines. Moreover, the input audio data is recorded so that the user can listen to his performance. Java Sound returns a software mixer to control the input and output lines. With this functions

```
INPUT line = (TargetDataLine) mixer.getLine(targetInfo);
OUTPUT line = (SourceDataLine) mixer.getLine(sourceInfo);
```

we obtain the lines through which we record and play the samples. To read samples from the input buffer we use the function

```
numberOfBytesRead = targetDataLine.read(byteData, 0,
        byteData.length);
```

where we can specify the number of bytes to read. Bytes will be further converted in double Java type for the signal processing. The bytes stored in byteData are then pushed in a buffer until the right frame length is reached (2048 sample = 4096 bytes).
For writing the frame to the output line we use

```
sourceDataLine.write(byteData, 0, numberOfBytesRead);
```

that let us specify the number of sample to write. Java Sound is then responsible for the correct playing.

jMusic

This part covers the MIDI functions for creating and playing the MIDI file. Once the frame has been processed and the necessary information are retrieved we need to create the single note object, provided by jMusic, to be added in the score. jMusic let us create a score where notes and rest can be added by simply specifying duration and the pitch (for the note):

```
note = new Note(note_pitch, note_duration); rest = new
        Rest(rest_duration);
```

As the analysis retrieve the fundamental frequency and the onset instant, the note is created and added sequentially to the score. This score will be used for visualizing the standard notation.

Metronome

A metronome is a device that produces regular clicks, settable in beats per minute. The metronome is a mandatory tool for every musician. It assists them in keeping a regular tempo while playing or practicing. We decided to implement the metronome as an extra feature to prompt users for using the application.
The metronome have been realized using the JavaSound MIDI package. A Synthesizer from MidiSystem has been created and opened, the MIDIChannel 10 has been retrieved (Channel 10 has all sorts of percussion instruments that make metronome sounds). With the metronome toggle button in the setting panel the user decide about the activation of the metronome. If so, as Rec button is pressed, a metronome thread is created. This thread starts and loops until the Stop button is pressed. In the loop cycle it occurs a noteOn MIDI message, a sleep of the thread, and a noteOff MIDI message: one beat of the metronome is played.
The metronome and the real-time playback threads are synchronized. If metronome is playing the playback thread is paused for the length of current frame plus the latency of the MIDI Synthesizer plus an estimate of the sound-card latency (about 20ms, this value is not retrievable from Java). This because when the metronome is playing, it has a higher priority with respect to the playback.

5.3.5 Visualization

In this section we illustrate the creation of the score notation.
As we explained, the score is created and we need to visualize it. The jMusic library visualize the score in a standard notation simply using the function:

View.notate(score);

This function produces an interface where score is shown as in Figure 5.7.

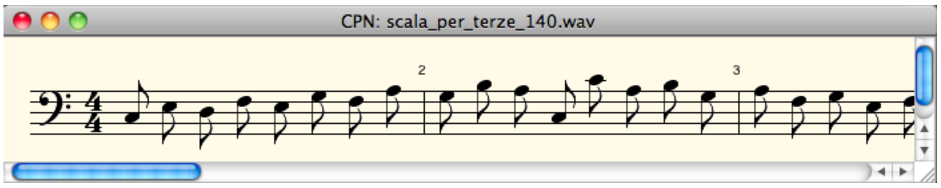


Figure 5.7: Score of a transcribed music excerpt

With the standard music notation, jMusic also provides an additional interface to make further changes to the score. As in Figure 5.8, an application menu is created to offer several possibilities:

- Open a new MIDI/jmusic/musicxml file.
- Save the current score to a MIDI / musicxml / jmusic file.
- Change the MIDI instrument or the timing of the song.
- Modify note's pitch and length: it is possible to correct/remove notes from the score.

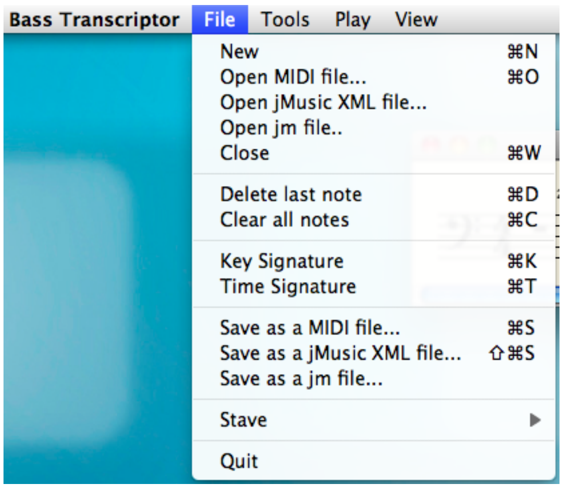


Figure 5.8: Application's menu for further score modification

jMusic do not provide the creation of the score in real-time and then we need to wait until the end of the performance to see the notation. We need to provide a direct feedback when the user is playing. In order to do this, we need to create a chart where a simplified notes representation could be presented. Using the jFreeChart library, a graph is realized where notes are added as they are played and retrieved. In this way a real-time feedback is provided to the user. In Figure 5.9 we can see the chart realized. The vertical axis represents the pitch of the notes while the horizontal is the time axis.

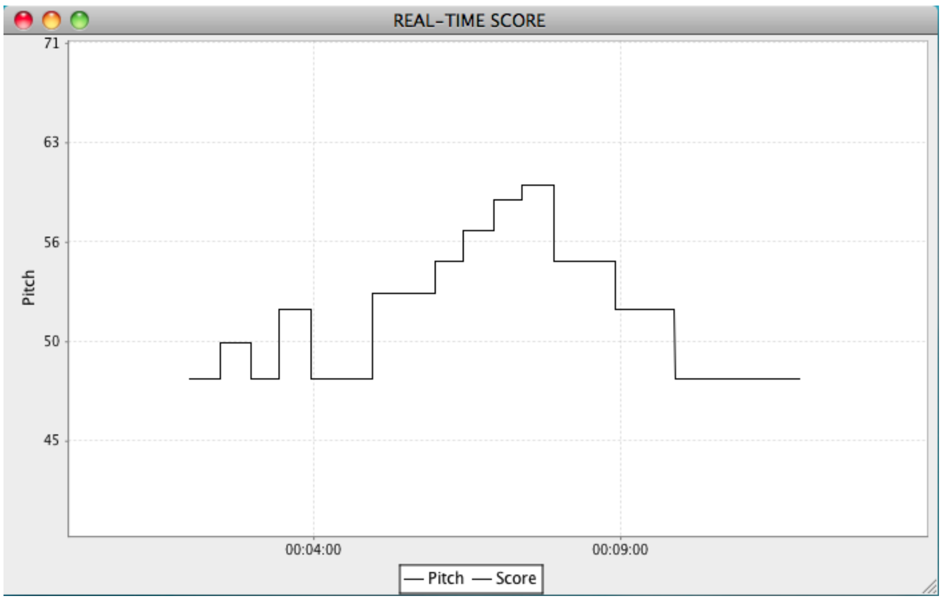


Figure 5.9: Real-time score representation

Chapter 6

Experimental Results and Evaluations

In this chapter we will show the experimental results and we will give an evaluation on the system.
Given that the application is realized to work both from audio file and for real-time performances, we need to test the system in both cases. The application has been tested with a synthesized dataset and by users. Objective and subjective results are provided.
In section 6.1 the datasets used for the test are illustrated. Section 6.2 shows the results performed on the testing dataset and by the single users. Section 6.3 contains considerations on the obtained results.

6.1 Dataset

In order to test the system properly we created a synthesized dataset and we let three people use the application. Then, we obtained their impresses about the application.

6.1.1 Synthesized Dataset

For testing purpose we created a dataset of ten bass lines. The audio files with the bass lines were created with a bass synthesizer using some effects to reproduce a real bass sound. The ten different pieces were realized with growing complexity as number of notes, timing, and presence of rests. The files have been sampled at 44100Hz and coded in PCM format at 16bit. In the next listing we explain a little each bass line created:

- bass line 01: quarter and half notes, beat of 100bpm, no rests;

- bass line 02: quarter and half notes, beat of 100bpm, with quarter and half rests;
- bass line 03: quarter and half notes, beat of 120bpm, with eighth, quarter and half rests;
- bass line 04: eighth, quarter and half notes, beat of 120bpm, with quarter and half rests;
- bass line 05: eighth, quarter and half notes, beat of 120bpm, with eighth, quarter and half rests;
- bass line 06: eighth, quarter and half notes, beat of 120bpm, with eighth, quarter and half rests;
- bass line 07: eighth, quarter notes, beat of 140bpm, with eighth and quarter rests;
- bass line 08: sixteenth, eighth, quarter notes, beat of 80bpm, with eighth and quarter rests;
- bass line 09: sixteenth, eighth, quarter notes, beat of 80bpm, with eighth and quarter rests;
- bass line 10: sixteenth notes beat of 100bpm, with sixteenth rests;

These files were then used to test the application.

6.1.2 Users Dataset

Three users tested the application with their own basses. They have been told to try the application and report everything concerning its working. Each user tried the application for about fifteen minutes. In this period the user needed to understand how to interact with the application, to plug the bass, to play and check the results of the transcription. They played three bass lines each, with a variable duration between 10 and 30 seconds. As we will explain later, users have different skills and approaches to music and this influenced the execution and the choice of the bass lines.

6.2 Results

In this section the results of the tests are provided.
As the application provides two different kind of use, we have two different

results: one objective and one subjective. Objective results have been calculated statistically testing the system with the datasets. Subjective results come up from the users' impresses on the application use.

6.2.1 Objective

The algorithm has been tested twice with the synthesized dataset and with the bass-lines played by the users. In both cases the measures used for each song to evaluate the transcription performance are Precision (P), Recall (R) and F-measure (FM), which is the weighted harmonic mean of the Precision and Recall.
This statistical measures are represented by the following equations:

$$P = \frac{TP}{TP + FP} \tag{6.1}$$

$$R = \frac{TP}{TP + FN} \tag{6.2}$$

$$FM = 2 \cdot \frac{P \cdot R}{P + R} \tag{6.3}$$

Where:

- TP: true positive, is the number of notes correctly retrieved;
- FP: false positives, is the number of notes with doubling/halving error;
- FN: false negative, is the number of notes wrongly retrieved

The Precision value represents the number of correct notes among all the retrieved.
Recall is the number of correct note retrieved among all notes in the music excerpt.
F-Measure it's a weighted mean of precision and recall.

Synthesized results

The system has been tested with all the songs in the synthesized dataset and statistics have been calculated.
In table 6.1 results are shown:

Test Name	Precision	Recall	F-Measure
Bass-line test 01	1	1	1
Bass-line test 02	0.972	0.972	0.972
Bass-line test 03	1	0.972	0.986
Bass-line test 04	0.972	0.972	0.972
Bass-line test 05	0.976	0.93	0.952
Bass-line test 06	0.952	0.909	0.93
Bass-line test 07	0.976	0.87	0.92
Bass-line test 08	0.978	0.849	0.909
Bass-line test 09	0.957	0.789	0.865
Bass-line test 10	0.957	0.692	0.804
Mean	**0.973**	**0.89**	**0.931**

Table 6.1: Results of the algorithm performance with the synthesized dataset

Users' results

With users' performances we did the same work of the synthesized database and statistics have been calculated. In Figure 6.2, 6.3, 6.4 results for each user are shown.

Test Name	Precision	Recall	F-Measure
User1 test 01	1	0.8	0.889
User1 test 02	0.968	0.811	0.882
User1 test 03	0.972	0.897	0.933
Mean	**0.98**	**0.836**	**0.900**

Table 6.2: Results of user1 performance

6.2.2 Subjective

We took in account the user's opinion about the application, so we let use the system by three people. We chose people to have a most wide possible user scenario: from the professional to the entry-level music player. We

User2 test 01	0.946	0.946	0.946
User2 test 02	0.952	0.93	0.941
User2 test 03	0.93	0.909	0.92
Mean	**0.942**	**0.928**	**0.935**

Table 6.3: Results of user2 performance

User3 test 01	0.93	0.816	0.87
User3 test 02	0.938	0.849	0.891
User3 test 03	0.918	0.763	0.833
Mean	**0.928**	**0.809**	**0.864**

Table 6.4: Results of user3 performance

obtained their subjective impress on the overall usability of the application, from the user interface to the resulting transcription. A brief introduction to each user is presented:

- user1: entry-level music player. His music playing knowledge is very poor, but he would like to start studying the music notation to write what he plays.
- user2: amateur bass player. He studied music theory and bass for few years. He likes to play for pleasure only.
- user3: professional musician. He plays bass and guitar as well. He studied bass for 10 years and he's a bass teacher for youth players.

In this section we simply relate the subjective user review on the application.

- user1: "This kind of work lets entry-level players to start from theory and not only from practice. In my opinion, it could be a great help in studying the notes position on the score. I think the transcription is good but my playing level is very low."
- user2: "The user interface is nice and very simple. I didn't had any problem in using the application. I just plugged the bass and played some bass lines: the system reacted well and I could immediately have my part written. My bass lines are simple and my way of playing is easy-going, I found the transcription almost faithful to what I played. I also listened back both to the transcribed part and to my recorded performance...better if I go back studying."

- user3: "I think the application still has some problems but, in my opinion, it has great capability. I think its best use is for transcribe, in a while, a melody you have in your head. In few seconds the application lets you set up the beat and record and write down the part. Yes, there are some problems with the note's duration and the halving and doubling errors, but you can edit the part on the instant. In a future version it could be great to add support for slap, slides and hammer-on techniques. But it is great. I think it could achieve very good results because it's very useful. Good job!"

6.3 Algorithm's evaluation and comments

The system has been tested with the dataset created and also with an in-line bass playing. Encouraging results were obtained in both cases.
In tables 6.1-6.4 we can see the performances of the algorithm proposed. In general we have good results.
The high precision values mean that the system find the right fundamental frequency more than 90% of the time in both cases. We can see that this value goes down when fast notes occours.
In case of the users performances the recall is slightly lower then with the synthesized dataset: this depends on the way of playing of each user. A more clear an shaped note is better retrieved, while tentative notes are wrongly or not retrieved. The synthesized dataset does not contain errors and the sound is the most clear possible: for these reasons the recall is higher in this case.
The f-measure confirm this results with a mean of 88% of good algorithm performances.
Nevertheless, some errors were noticed: these may be caused by the pitch detector or by the onset detector.
We first see the pitch detector algorithm errors:

- Pitch Halving: it could happen that the algorithm wrong octave. A note on a octave is identified but one octave lower. This happen specially when fast notes occur.

- Pitch Doubling: it's the opposite of the halving problem. A note on a octave is identified at one octave higher.

In table 6.5 and 6.6 the Doubling/Halving errors are shown for both cases.

Test Name	Doubling & Halving Error
Bass-line test 01	0
Bass-line test 02	0.027
Bass-line test 03	0
Bass-line test 04	0.027
Bass-line test 05	0.022
Bass-line test 06	0.043
Bass-line test 07	0.021
Bass-line test 08	0.018
Bass-line test 09	0.033
Bass-line test 10	0.029
Mean	**0.0220**

Table 6.5: Doubling and halving errors for the synthesized dataset

Test Name	Doubling & Halving Error
User1 test 01	0
User1 test 02	0.026
User1 test 03	0.025
User2 test 01	0.051
User2 test 02	0.044
User2 test 03	0.063
User3 test 01	0.057
User3 test 02	0.053
User3 test 03	0.063
Mean	**0.0424**

Table 6.6: Doubling and halving errors for the user dataset

Onset detector errors:

- Note length: a wrong duration of the note is set. This kind of errors are caused by the onset detector. The pick picking algorithm of the onset detection has been created experimentally and this may be the cause of errors on notes duration.

Other kind of errors:

- Non-existing notes: it happens few times that the system retrieve non-existing notes. This can be caused by the initialization of the audio driver in Matlab (not in Java) that produces some clicks, or by some noise in the audio file.
- Latency (measure of time delay in a system): in Matlab long latency has been experienced with plugged-in bass while hearing back what playing. This has been solved porting the application in Java with better management of the audio resources.

Chapter 7

Conclusions and future developments

7.1 Conclusions

Due to the wide diffusion of digital audio formats on the web in last few years, our way to produce, listen to and search for music is progressively changing. Automatic music transcription is one of the main topic in audio research. Our work attempts to solve the problem of real-time automatic music transcription of a bass-guitar instrument in a monophonic context. Many applications in commerce perform automatic instrument transcription, but no one in real time and specific for bass. The goal of our thesis was to realize a real-time bass transcription system. The core of the application is the pitch detection algorithm based on the Combined Difference Function, proposed as an improvement of the Yin algorithm. In this work all the details, from the algorithm mathematical background to the application development, have been presented.
As initial requirements, our goal was to create a simple to understand and effective application. The system should perform the transcription in real-time and give an instant feedback to the final user. Additionally, some more features were added to improve the user experience, like the metronome, the audio playback and the MIDI files creation.
In Chapter 6 results are presented in an objective and subjective form. The application achieved interesting results both in performances and usability. Two types of dataset were created for the tests: one composed of synthesized bass-lines and one of few live performances of three users.
Objective evaluations tell us about the goodness of the performances of the

algorithm, validating what we expected. The doubling and halving errors rate are similar to the results in the original papers and the precision obtained is very high. We noticed that the recall depends much on the user's way of playing. More clear and noiseless are the notes played, more effective is the transcription. This is validate also from the synthesized dataset that provides better results, because of the perfect played bass-lines.
Making a comparison between the initial requirements and the user experience the results are very interesting. Users remain satisfied by the overall feeling with the application. As no a-priori information was provided, each user understood by himself how the system worked and tested the system with its own bass. The impresses obtained are much positive about the interface, its usage and the general feedback of the system. Also transcriptions were faithful to the users' performances. Despite this, few problems raised with particular playing technique such as slap, pop, sliding, vibratos and hammer-on/pull-off, but the application is not focused on those techniques which need specific methodologies. The overall results are positive and the application created works with good performances: in the next section we describe the possible future developments of the application

7.2 Future developments

The purpose of the thesis was to create an application for a variety of users: from the entry-level bass player to the professional musician. We can think to this application as a mix of a music composition and a learning software. Nevertheless, the application could be improved to add support for missing techniques as slap, pop, sliding, vibratos, hammer-on and pull-off. The polyphonic case (more notes played together) also should be taken in account: it often happens to use chords, or bi-chords, in a live performance. Further more, more functionality can be added to the application, as the possibility of saving the live performance, adding some effects or retrieve the tablature. As users said, one of the best usage is "for transcribe, in a while, a melody that we have in our head". In this sense, the application can be used to create a database of bass phrases that can be played in different situations. The database itself can be used for cataloging and for studies on melodies. As another possibility a learning application could be created: lessons and exercise with a real-time feedback and valuation on what the student is playing.

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