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Kinematic synergies in upper limb daily life movements and their application for rehabilitation exoskeleton motion planning

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Abstract

Upper limb exoskeletons have been recently implemented in the rehabilitation for people with upper limb disabilities, which may be caused by strokes or spinal cord injuries.

Even though this innovative technology can improve the way treatments are performed, few efforts have been made to manage a movement control based on kinematic synergies, so that it well matches the body characteristics.

The purpose of this project was to individuate such kinematic synergies in daily life activities and attempt to verify if they could be the key for the motion planning of the robotic assistive device.

Sixteen different individuals were asked to repeat six different motor skills which tried to recreate daily life activities.

Those results were studied to try to identify kinematic synergies in the movements.

The choice for the recognition approach went to the Principal Components Analysis (PCA), after extensive research on papers connected to the topic.

Once the synergies were found, they were investigated to assess their spatial and temporal aspects.

The last analysis performed was recreating the end effector position path using the principal components and compare it with the original one.

The results obtained from this reconstruction step confirmed that the kinematic synergies could be used for the motion planning of the exoskeleton, as the trajectory of the end effector was comparable with the original one.

It was also possible to observe that each principal component had a specific contribution to the creation of the trajectory.

Keywords: kinematic synergies, upper limb, exoskeleton, rehabilitation, PCA, motion planning

Abstract in italiano

Gli esoscheletri per gli arti superiori sono stati recentemente implementati nella riabilitazione di persone con disabilità agli arti superiori, che possono essere causate da ictus o infortuni alla spina dorsale.

Anche se questa nuova tecnologia può migliorare il modo in cui vengono eseguiti i trattamenti, sono stati fatti pochi sforzi per gestire un controllo del movimento basato sulle sinergie cinematiche, in modo che si adatti bene alle caratteristiche del corpo.

Lo scopo di questo progetto è stato quello di individuare tali sinergie cinematiche in attività svolte nella vita quotidiana e cercare di verificare se possano essere la chiave per la pianificazione del movimento del dispositivo robotico di assistenza.

A sedici persone diverse è stato chiesto di ripetere sei diverse attività motorie che cercavano di ricreare dei movimenti fatti quotidianamente.

I risultati sono stati studiati per cercare di identificare le sinergie cinematiche nelle attività.

La scelta dell'approccio di riconoscimento è ricaduta sull'Analisi delle Componenti Principali (PCA), dopo un'ampia ricerca su articoli legati all'argomento.

Una volta individuate le sinergie, queste sono state analizzate per valutarne gli aspetti spaziali e temporali.

L'ultima indagine effettuata è stata quella di ricreare l'andamento della posizione dell'effettore finale utilizzando le componenti principali e confrontarla con quella originale.

I risultati ottenuti da questa fase di ricostruzione hanno confermato che le sinergie cinematiche possono essere utilizzate per la pianificazione del movimento dell'esoscheletro, poiché la traiettoria effettuata dell'effettore finale è paragonabile a quella originale.

È stato inoltre possibile osservare che ogni componente principale ha dato un contributo specifico alla creazione del percorso.

Parole chiave: sinergie cinematiche, arti superiori, esoscheletro, riabilitazione, PCA, pianificazione del moto.

Contents

1 Introduction

1.1. Background and motivation of the work

Neurological damages, such as strokes, spinal cord injuries, or neurodegenerative disorders can comport the loss of abilities in sensor-motor activities, damaging the execution of everyday tasks, with the result of affecting the quality of life.

Strokes, specifically, are caused by an interruption of blood flow to the brain, resulting in damage to neural cells, and can be fatal.

In Italy, stroke is the third leading cause of death, after cardiovascular diseases and neoplasms, but the first absolute cause of long term disability: strokes affect approximately 185,000 people every year; of these 150,000 are new cases, while 35,000 are cases that recur after the first episode. (www.humanitas.it, s.d.)

Seventy-five percent of stroke cases affect people over 65 years, but it is a disease that also bear upon the younger population (www.humanitas.it, s.d.).

The survivors of stroke can experience paralysis or loss of physical strength on one side of the body (hemiparesis) as well as memory problems making it difficult to perform activities of daily living (ADL).

Rehabilitation is the main treatment for these disabilities, a process that allows the stroke patients to relearn the best possible use of their limbs and regain independence.

These kinds of treatments can continue throughout most of the stroke patients' life and because of that, they can be labor-intensive and costly.

Therapy is most successful when administered quickly after a stroke, but this is not always possible.

Additionally, research has shown that task-based exercises and intensive therapy have a considerable positive impact on motor recovery (Fink, "Recovery from stroke: current concepts and future perspectives,", 2020).

Following acute stroke rehabilitation, stroke survivors' physical therapy continues to show improvements, indicating that recovery may last for many years.

Due to its labor-intensive nature, treating patients with sufficient rehabilitation care is only going to get tougher to be sustainable for the healthcare system, if the people suffering from strokes keeps increasing. (Fink, "Recovery from stroke: current concepts and future perspectives,", 2020)

Stroke usually have motor consequences in terms of impairments. In particular, upper limbs rehabilitation has gained interest, given the high cost in terms of hindered daily life activities derived from upper limbs disability.

A recent innovation to the standard manual care performed on patients has been the use of robotic devices.

These kinds of devices can perform repetitive tasks that the therapists cannot do for long time without practice and the interaction between the assistants and the device, can improve the effectiveness of the activity (M. Xiloyannis, 2022).

Over the years, many kinds of wearable systems for upper limb rehabilitation have been developed by engineers.

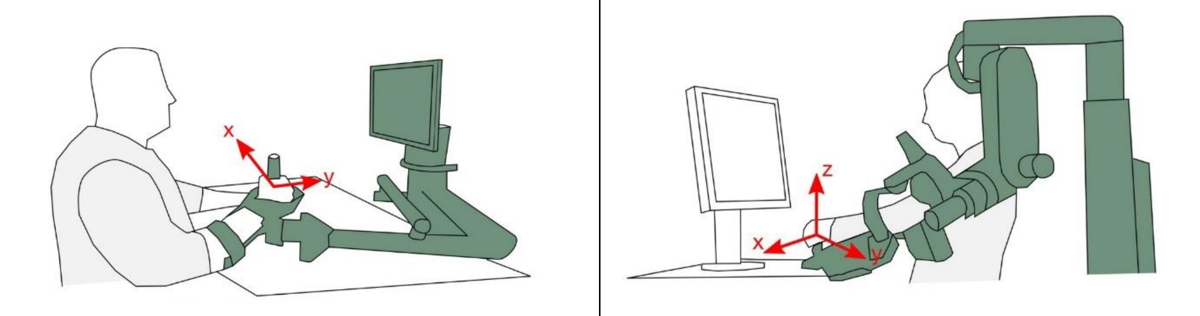
The first introduced devices were the end effector robots, which assisted the users in 2D plane movements, such as The 'Bi-Manu-Track (Reha Stim)' and the 'Haptic Master (Moog Inc)' which are commercially available. (H. I. Krebs, 1998)

Another example is the In Motion Arm by Bionik (M. Xiloyannis, 2022) ,which can be seen in Figure 1(a).

Since those early introduction, there have been two main breakthroughs in this field. The first one was the introduction of the use of rigid exoskeletons, which could help people execute movement in a 3D space and control different degrees of freedom. (P. Maciejasz, 2014)

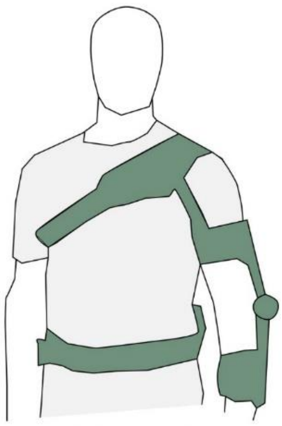
In that category can be found the 'Armeo Power by Ocoma' (M. Xiloyannis, 2022), present in Figure 1(b).

After that, developed during the 2010s, researchers added exosuits to the scenario, like the one in Figure 1(c), and they were the first step in the direction of soft-robotics wearable devices. (M. Xiloyannis, 2022)



(a) End Effector

(b) Exoskeleton



(c) Exosuit

Figure 1: Some examples of wearable devices obtained from the work of. Proietti etc from 2022 (T. Proietti E. A., 2022)

Those three distinct kinds of rehabilitation devices can be classified in many ways: for example, the DOFs controlled, the actuation system, the type of control system, and the portability. (T. Proietti E. A., 2022)

For what concerns the interaction with the users, there are two main categories: active (powered) and passive (unpowered) devices.

Active devices can produce additional torque and they can transmit it to the assisted limb using, most of the time, an electric actuation system (i.e., DC motors) or a pneumatic one. As an alternative, passive devices, store energy from a different kind of source, like springs, just to support motions, without an additional source of energy.

Given the fact the user must re-add the energy, these types of devices are used for healthy end-users, for example, to improve ergonomics and reduce injuries.

Additionally, they are exploited to support mild impaired subjects, providing a gravitational support.

Their advantages are that they are lighter than their active counterparts and less expensive.

Another possible classification focuses on control strategies. There are several approaches to control these devices (T. Proietti V. C.-B., 2016), using distinct kinds of algorithms, and in most of the cases the management of the movement is handled joint per joint.

Various techniques were attempted in trying to solve that task, improving the results and the common issue of redundancy. (T. Nguyen, 2021)

However, in the last few years, different studies have been trying to find a diverse approach, inspired by how our brain works.

The neural system does not focus on a joint per joint control but rather manages movements handling synergies. (al A. L., 2016) (B. J. Stetter, 2020)

Because of that, many scientists have been trying to replicate this controlling behaviour in the exoskeletons, trying to create a simpler strategy and a motion based on the joint kinematic characteristics of the user.

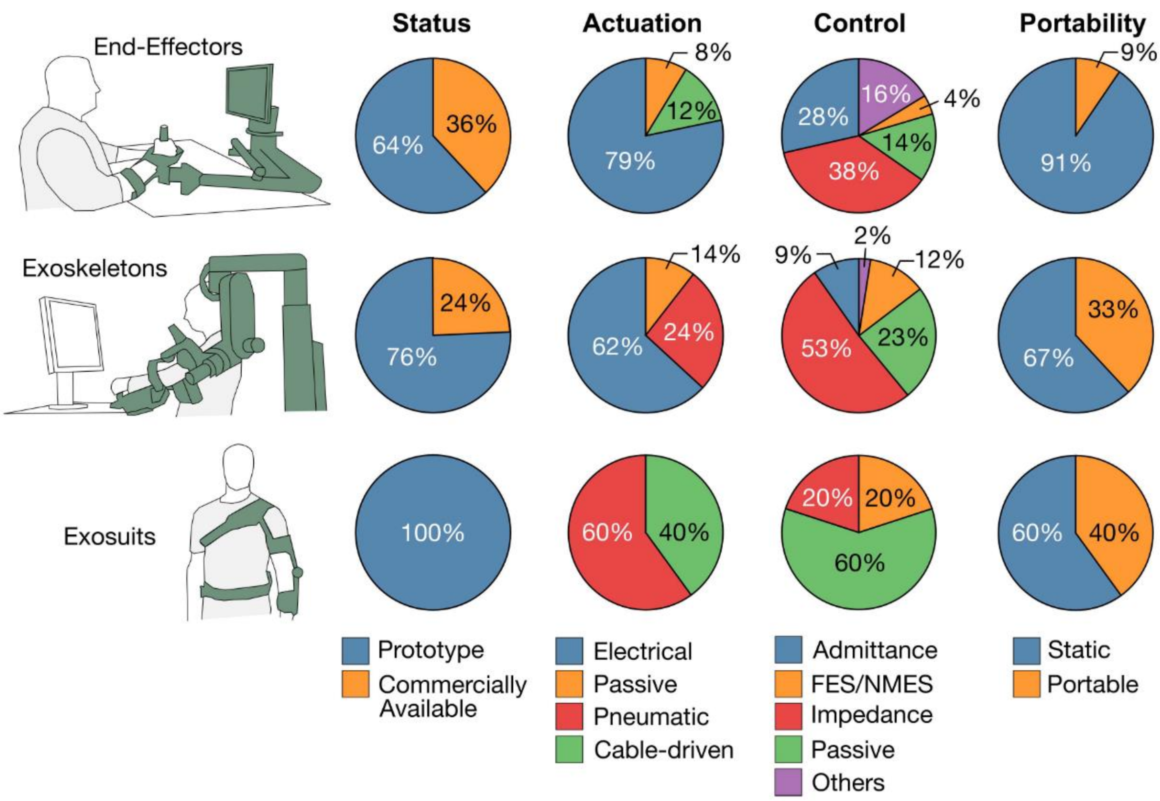


Figure 2: Overview of the situation regarding up-to-date devices, as analysed in (T. Proietti E. A., 2022)

1.2. Related works

During the last few years, researchers have worked on a way to identify kinematic synergies to use them to handle the wearable device the patient is using with the goal of producing a simplified control scheme for high DoF devices. (M. Burns, 2017)

The most relevant works identified in the scientific literature follow these development steps:

- analysis of the methodology to identify the interactions between joints, in the tasks made by the users;
- test of the developed solution which uses synergies;
- assessment of the error in the outcomes to evaluate the effectiveness of the technique with respect to the classical approach.

All the analyses are performed individual per individual as a personalized control strategy for assistive exoskeletons is the best way to perform rehabilitation, compared to a generic approach. (R. Garcia-Rosas Y. T., 2021)

The methodologies identified in the scientific literature to calculate kinematic synergies include Principal Component Analysis (PCA), singular value decomposition (SVD), non-negative matrix factorization(NNMF) and many others approaches.

PCA is the most common methodology, as it allows to find patterns in the research outputs and detect the synergies.

The scientific literature often relate the kinematic synergies to the muscular ones, as they work together to control a movement.

For instance, in "Identification of Human Shoulder-Arm Kinematic and Muscular Synergies During Daily-Life Manipulation Tasks" (T. Hu, 2018), the analysis is performed over thirty different daily-life activities.

The goal of that work is to understand the influence of these 'chains' in the movements, to be able to use them in the control of rehabilitation exoskeletons.

This paper chooses PCA between different machine learning techniques like NNMF and Auto Encoders (AE).

The results showed that PCA was indeed an excellent choice for the identification of the synergies as, once obtained, they cover the 95% of variance in the data.

An alternative to the previous paper, which still focuses on the relationship between muscular and kinematic chains, is "On identifying kinematic and muscle synergies: a comparison of matrix factorization methods using experimental data from the healthy population" (Loos, 2017).

In this study, different algorithms were considered to detect the synergies in the data, but this time, all of them were used and the results were compared to see which one was the best choice.

In particular, the three methods applied were (PCA), (NNMF), and independent component analysis (ICA).

It was shown that PCA and NNMF had a similar performance on both EMG and joint motion data, and both outperformed ICA. In addition, it was demonstrated that PCA vectors describe the major direction of the data while NNMF vectors describe the edges of the data.

A further publication, which was found extremely helpful for this project, was "Kinematic Synergy of Multi-DoF Movement in Upper Limb and Its Application for Rehabilitation Exoskeleton Motion Planning " (al S. T., 2019).

In this document, the authors tried to investigate the presence of the kinematic synergies in reaching movements, by tracking the data of the arm during the executions of the tasks thanks to a motion capture system.

PCA was used to derive kinematic synergies from the activity made by each subject. After that, a 4-Dof exoskeleton was designed in SolidWorks to simulate the control of such device, using the synergies.

The results showed that the principal components extracted from the data, contributed in a specific way to end effector position and accurately describe the dynamic profile of the original angles.

These outcomes further confirmed the importance of the synergies in the motion planning of a multi-DoF exoskeleton, which can be simplified if this approach is followed as the number of variables under control is smaller.

On the other hand, some studies illustrated an alternative method to the Principal Components Analysis.

An example is "Task-space Synergies for Reaching using Upper-limb Prostheses", which focused on using a synergistic relationship expressed in task space. (R. Garcia-Rosas D. O., 2020)

The authors investigated this innovative approach as it could replace the necessity of personalization and task calibration, with a model-based method that requires the individual user's arm kinematics and the anticipated hand motion during the task.

The experimental results they obtained, evaluated on forward-reaching tasks, proved that this technique achieved comparable outcomes to its alternative, which instead used the joint's space.

Those solutions avoided the need of the intermediate step of the calibration process, which can be time-consuming.

From the same authors, there was also one more interesting paper, which described an additional method to assess the use of kinematic synergies to control an exoskeleton.

This article, titled "On the Relationship Between Human Motor Control Performance and Kinematic Synergies in Upper Limb Prosthetics" (R. Garcia-Rosas D. O., 2018), provided an approach in which they implemented a model of the kinematic synergy.

This reference was integrated with a cost function to prove the importance of using online optimization methods to identify these chains in the movements.

The source they chose for the synergy was a shoulder-elbow linear one, which has been detected to appear during reaching movements.

To be able to achieve their goal, they added a cost function that captured the aim of the reaching task for each synergy.

The results highlighted individual variability in performances and showed that as the task is learned during the repetitions, the properties observed are suitable for the use of online observation methods.

Those algorithms are then applied to identify the synergies which maximise the performances.

Thanks to the repetitions of reaching tasks, the quality of the synergies obtained were compared to find the best model to describe them.

The same research group provided a further approach, called "Personalized Online Adaptation of Kinematic Synergies for Human-Prosthesis Interfaces ". (R. Garcia-Rosas Y. T., 2021)

As cited before, this article remarks on the importance of personalization of the synergy setting to have an effective rehabilitation device.

Specifically, the authors present two main subtasks to reach such a goal:

- The process of human motor adaptation;
- The variation in motor learning dynamics of individuals.

To solve those issues, the researchers proposed a technique made of two-steps:

1. the use of an optimal personalized parameters;
2. an online optimization scheme to detect the optimal synergies in the experiments accomplished.

Their results showed that the algorithm chosen was effective in obtaining optimal synergies with a high uniform convergence velocity amongst a set of individuals.

The main work found in the scientific literature is summarized in Table 1.

Most of the contributions focused on using techniques like PCA to identify the kinematic synergies in their data.

The inputs for their analysis were obtained from experiments in which the subjects were asked to execute tasks that represent daily life activities, so for example reaching movements or grasping objects.

Even though PCA was the most common methodology, a group of scientists tried to take a different approach, creating a series of connected papers seeking the best way to perform rehabilitation with exoskeletons.

Name of the publication	Approach used to identify kinematic synergies	Task effectuated (reaching, grasping…)	Quality assessment approach used (RMSE…)	Authors
Identification of Human Shoulder-Arm Kinematic and Muscular Synergies During Daily-Life Manipulation Tasks (T. Hu, 2018)	Machine learning techniques. (PCA, NNMG, AE)	Thirty different tasks, three repetitions each	Based only on the percentage of variance collected	Tingli Hu, Johannes Kuehn, and Sami Haddadin
On identifying kinematic and muscle synergies: a comparison of matrix factorization methods using experimental data from the healthy population (Loos, 2017)	Three factorization methods considered in this paper are principal component analysis (PCA), nonnegative matrix factorization (NNMF), and independent component analysis (ICA)	Symmetric bimanual reaching motions, i.e., the two hands move synchronously in horizontal and vertical directions.	The8pplicay of the algorithms was assessed using six different metrics divided in three categories: the first two regarded the structure of the data, the second 8pplice the quality of the reconstruction and the last two the correlation of the original and the reconstructed dataset	Navid Lambert-Shirzad and H. F. Machiel Van der Loos

Kinematic Synergy of Multi-DoF Movement in Upper Limb and Its Application for Rehabilitation Exoskeleton Motion Planning (al S. T., 2019)	Principal component analysis (PCA) was used to derive kinematic synergies from the reaching task for each subject.	The participants were asked to execute reaching tasks to clicks some buttons.	The quality of the representation of the synergy was based only on the percentage of variance collected.	Shangjie Tang, Lin Chen Xiaoyig Wu , Long Bai, Michele Barsotti, Lintao Hu, Antonio Frisoli , Yongqiang Li and Wensheng Hou
Differences between kinematic synergies and muscle synergies during two-digit grasping (M. Tagliabue, 2015)	Principal component analysis (PCA, temporal or static) was performed.	"The analysis was subdivided into three epochs: reach, grasp-and-pull, and static hold"	This paper was more focused on a finding a correlation between kinematic and muscle synergies instead of evaluating the quality of the reconstruction made with the kinematic synergies.	Michele Tagliabue, Anna Lisa Ciancio, Thomas Brochier, Selim Eskiizmirliler, Marc A. Maier
Inter joint coupling and joint angle synergies of human catching movements	"We applied PCA to determine the amount of inter-joint coupling and the	Human catching movements	RMSE was used to compare and evaluate the quality of the reconstruction based on the synergies	Till Bockemül , Nikolaus F. Troje, Volker Dürr

(T. Bockemühl, 2010)	number of effective DoFs underlying human catching movements that involve a 10D joint angle space. "			
Task-space Synergies for Reaching using Upper-limb Prostheses (R. Garcia-Rosas D. O., 2020)	In this work, an alternative synergy-based strategy, using a synergistic relationship expressed in task-space, is proposed.	Forward reaching task using with an elbow prothesis	Six different metrics were used: Two metrics of task performance were used: completion. Time and reach terminal error. Two metrics of quality of motion were used: path smoothness and variability. Two metrics of motor behaviour were used: hand/joint path difference and upper-body displacement.	Ricardo Garcia-Rosas ,YingTa , Denny Oetomo , Chris Manzie , and Peter Choong
On the Relationship Between Human Motor Control	"Kinematic synergies have been shown as an alternate	Subjects performed a center-out forward reaching task	"A widely accepted method for modelling trajectory planning and generation in the	Ricardo Garcia-Rosas ,YingTa , Denny

Performance and Kinematic Synergies in Upper Limb Prosthetics (R. Garcia-Rosas D. O., 2018)	method where the motion of the prosthetic device is coordinated with that of the residual limb.”	from a seated position while using a virtual synergistic prosthetic elbow.	CNS is to characterize motor control performance with a cost function which is optimized to determine the desired hand trajectory.”	Oetomo , Chris Manzie , and Peter Choong
Personalized Online Adaptation of Kinematic Synergies for Human-Prosthesis Interfaces (R. Garcia-Rosas Y. T., 2021)	“A scalar linear relationship between the velocity of the shoulder and elbow flexion for the task of reaching forward is selected in this paper as the specific example of kinematic synergy to exemplify the11pplication of the method presented herein.”	“The experiment required subjects to perform a center-out forward reaching task between two static targets in a VRE while using a virtual synergistic prosthetic elbow.”	“Validation was performed through the comparison of the mean square error (MSE) between the response of the identified underlying model and the validation dataset for different system orders”	Ricardo Garcia-Rosas ,YingTa , Denny Oetomo , Chris Manzie , and Peter Choong

Table 1: Overview of the related works found on the internet.

1.3. Objective

Given all the relevant scientific literature, the goal of this project is to study the kinematic synergies in upper limb daily life activities to find their applications in rehabilitation using robotic exoskeletons.

Controlling the exoskeletons motion system focusing on those principal components, would simplify the way it works as the number of variables to control decrease.

Additionally, it would manage it in a way that takes more into account the joint kinematic characteristics of the user.

The choice of the investigation method to detect the synergies went to the Principal Components Analysis, in view of the vast literature supporting this approach.

Following the analysis steps, in which the principal components are going to be assessed on spatial and temporal aspects, the focus is going to shift on the reconstruction of the trajectories using them, to see how accurately would work the motion planning process of the exoskeleton with this specific approach.

2 Data-set

The following chapter describes the experimental procedure set to be able to analyse the kinematic synergies in activities of daily living (ADLs).

All the steps were developed in a previous work in the lab where I performed my thesis, and they are described in the paper "A unified scheme for the benchmarking of upper limb functions in neurological disorders" (al V. L., 2022).

2.1. Kinematic model

The kinematic model proposed by the paper was inspired by a previous work called "Upper-limb powered exoskeleton design." (Perry JC, 2007)

Additionally, they balanced the trade-off between complexity and accuracy and followed the instructions given by the International Society of Biomechanics (ISB) (Wu G, 2005).

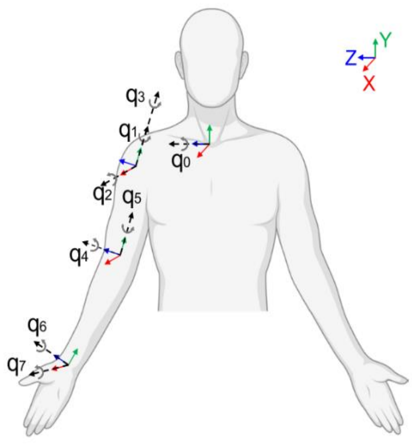


Figure 3: Upper limb kinematics model according to ISB guidelines, from (al V. L., 2022)

In detail, the thorax is represented by a single DOF corresponding to trunk flexion/extension -(q0). The shoulder is simplified as a ball-and-socket joint represented by the glenohumeral joint.

The corresponding three shoulder DOFs are plane of elevation -(q1), elevation angle -(q2), and axial rotation -(q3).

Two DOFs represent the elbow movement: flexion/extension -(q4) and pronation/supination (i.e., axial rotation of the forearm— q5). Finally, the wrist is characterized by two DOFs: flexion/extension -(q6) and ulnar/radial deviation -(q7).

2.2. Experimental Protocol

Sixteen healthy subjects were asked to make six different motor skills (also called tasks), defined as a sequence of distinct motor primitives.

These motor primitives, considered as sort of building blocks of the tasks are (Table 2):

- Idle;
- Stabilize;
- Point to Point reach;
- Reach for grasp;
- Transport;
- Reposition.

Motor primitive	Definition
Idle	Holding the upper limb in a stable position without contact with any object
Stabilize	Holding a target object still. There is the grasp of a target object throughout the minimal motion
Point-to-point reach	Reaching a target point without contact with any object
Reach for grasp	Reaching a target object and contact it through grasping
Transport	Moving a target object in space
Reposition	Moving away from the target object toward the idle position, without contact with any other object

Table 2: Upper limb motor primitives

These six motor primitives were combined to define three different groups of motor skills, which represented the most common activities considered in clinical evaluation and were: i) *anterior reaching, ii) moving objects and iii) hand to mouth.*

For all the motor skills, the subject was seated in front of a desk on a chair without an armrest and with the seatback blocked with a tilt angle between 100° and 110°.

The starting position was with the hand on the desk in a comfortable position, with the palm down and with the center of the palm of the hand aligned with the user's navel (A—rest position) (Figure 5).

(a) Front view

(b) Lateral view

Figure 4: Rest position (A) views, from (al V. L., 2022)

The height of the desk was adjusted to have the elbow at 90° of flexion and no compensation of the shoulder in the frontal plane when the subject had the arm in the rest position.

If the subject could not reach this position autonomously, the rater could passively position the patient's arm in the starting position.

As to the target points, in the anterior reaching and move objects motor skills, they could be placed at two different heights, according to the assessor's choice: at the same height of the rest position or the subject's shoulder height.

The rest point, instead, did not change.

Consequently, these motor skills were split into (1) anterior reaching at rest position height, (2) anterior reaching at shoulder height, (3) move objects at rest position height, and (4) move objects at shoulder height.

The subject had to conduct the movements without moving his/her back away from the backrest to avoid compensation with the trunk. Movements were performed at a self-selected speed.

During the anterior reaching motor skills, both at rest position height and at shoulder height, starting from the rest position (A), the subject had to reach three target points placed in the central (B), contralateral (C), and ipsilateral positions (D) (Figure 6).

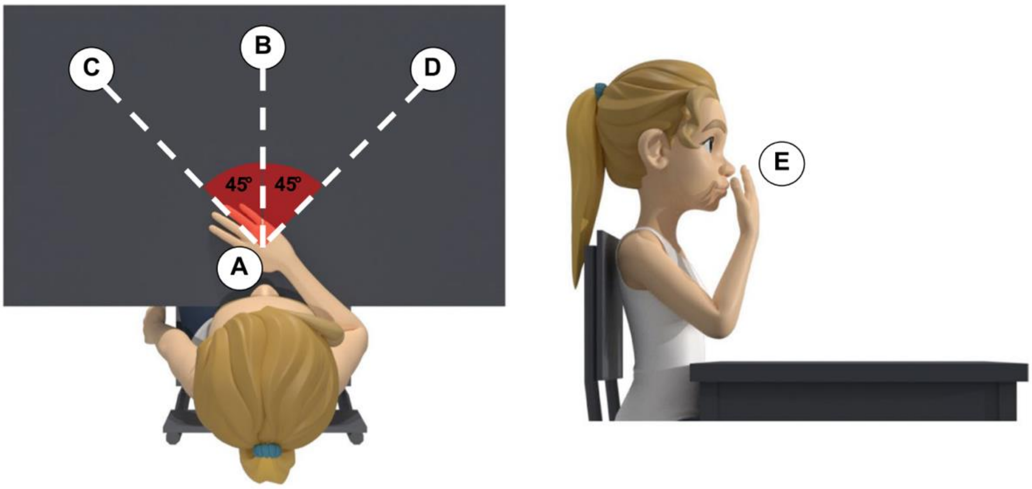


Figure 5: Target points or object location for motor skill anterior reaching and move object. From (al V. L., 2022)

A = Rest position; B = Central position; C = Controlateral position;

D = Ipsilateral position; E = Mouth

After each reach, the subject had to return to the rest position (A) (Table 3). Point B was placed in front of the subject and aligned with point A. Points C and D were located at 45 degrees with respect to the straight-line connecting point A with point B (Figure 6).

The three target points (B, C, and D) were placed at the distance corresponding to a complete elbow extension of the subject's arm in that direction.

In the moving objects motor skills, the starting position was the rest position (A), and the object was placed in the central position (B).

The subject had to grasp the object in the central position (B), then push/pull it to reach two target positions at contralateral (C) and ipsilateral (D) (Figure 6).

After each reaching, the subject had to release the object and return to the starting position (A). Lastly, the object was returned to the initial central position (B) (Table 3).

Finally, the hand to mouth motor skill was subdivided into two cases: without and with the object.

In the first case, starting with the hand on the desk in the rest position (A), the subject was asked to reach his/her mouth I and touch it with the palm. After the idle phase, the subject had to return to the rest position (A).

Instead, the case with the object consisted of the activity of daily living mimicking the drinking task.

Starting with the hand on the desk in the rest position (A), the subject had to grasp an object close to the rest position (A), reach his/her mouth I with the hand and the object, return to the start position on the plane (A), then release the object and position his/her hand in the rest configuration (Table 3).

During this task, the subject was asked not to move the head toward the hand.

The motor skill anterior reaching at rest position height represented the easiest movement that can be analysed, and it was suitable for patients unable to grasp objects or elevate their arm against gravity.

Motor skill	1) Anterior reaching at rest position height 2) Anterior reaching at shoulder height	3) Move objects at rest position height 4) Move objects at shoulder height	5) Hand to mouth without object	6) Hand to mouth with object
Motor primitives	1) Idle (A) 2) Point-to-point reach (B) 3) Reposition (A) 4) Point-to-point reach I 5) Reposition (A) 6) Point-to-point reach (D) 7) Reposition (A)	1) Idle (A) 2) Reach for grasp (B) 3) Transport I 4) Reposition (A) 5) Idle (A) 6) Reach for grasp I 7) Transport (D) 8) Reposition (A) 9) Idle (A) 10) Reach for grasp (D) 11) Transport (B) 12) Reposition (A)	1) Idle (A) 2) Point-to-point reach I 3) Idle I 4) Reposition (A)	1) Idle (A) 2) Reach for grasp (A) 3) Transport I 4) Stabilize I 5) Transport (A) 6) Reposition (A)

Table 3: Motor skills flow description through motor primitives

This motor skill, together with the motor skill move objects at rest position height, could have been performed by sliding the arm on the table.

The motor skills 'moving objects' and 'hand to mouth with object' involved the mobilization of an object.

To build a standardized and replicable benchmarking scheme, the object was represented by a cylindrical object of daily life (i.e., 0.5 l empty water bottle).

It was suggested to do at least eight repetitions for each motor skill as a compromise between data robustness and repeatability, and the time required for the protocol.

To be able to analyse the data related to each one of those motor skills, a motion capture system was used.

A total of fourteen markers were placed in strategic landmarks, as shown in Figure 7, such that they would be used to describe the angles evolution over time of the eight joints under analysis.

Marker placement:

- Left acromium
- C7
- Right acromium
- Lateral epicondyle of the elbow
- Medial epicondyle of the elbow
- Ulnar styloid
- Radial styloid
- Third metacarpophalangeal joint
- Tip of the medium finger

Plus three target points (one marker for each target point) and two markers on the base of the diameter of the object.

The description of the markers was the input of the work, in a form of database per each individual's motor skills.

For the purposes of the investigation regarding the kinematic synergies, those data were transformed into angles values over time, describing the eight joints defined in the experimental setup, thanks to a MATLAB (the MathWorks, Natich, MA, USA) code.

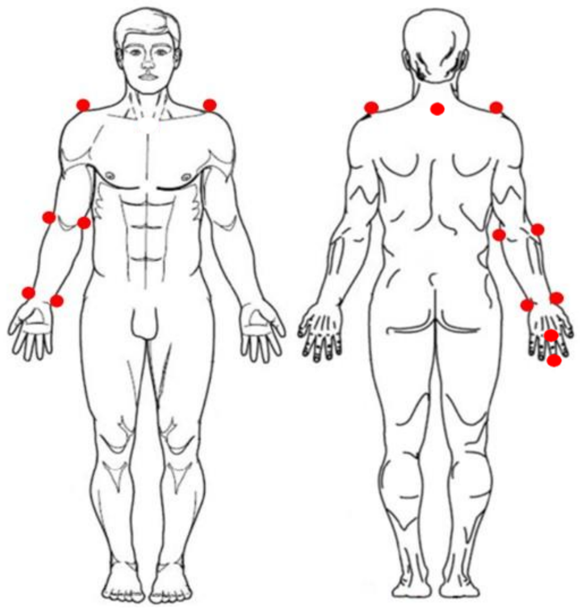


Figure 6: Markers placements

3 Research Structure

The following chapter is dedicated to the description of the analysis performed on the data obtained from the experiments of the publication "A unified scheme for the benchmarking of upper limb functions in neurological disorders " (al V. L., 2022), and described in the previous section.

3.1. Specific Objectives

The purpose of this project was to study kinematic synergies in basic upper limbs' daily life movements and reproduce them in a simulation environment, to be able to see if they could be used to control a rehabilitation exoskeleton.

Given that goal, different specific objectives were selected to be able to assess the developed methodology. Specifically, the investigation developed in this project was trying to clarify:

1. How many synergies are needed to describe the data?

2. How were characterized those synergies in terms of their relationship with the joints?

The features investigated were:

i. Which joints were the most influential in each synergy;
ii. Which joints were more correlated with the synergy;
iii. Which joints were coordinated in their movements .

As there were eight distinctive joints, seeing the difference between done in terms of importance and relations would have been remarkably interesting.

3. How much of the overall movement per joint did each synergy cover?

Once these features were found, the attention shifted to the amount of movement made by the synergy.

This subtask wanted to verify how much of the movement done by each joint during the motor skills, was covered by each one of the principal components identified.

4. To verify if the reconstructed trajectory by means of the synergies analysed in point one was accurate.

Checking the way the end effector's path was rebuilt, visually and using the RMSE (root mean square error), would allow to verify if the kinematic synergies could be the key for the motion planning process of the exoskeleton.

3.2. Methods

PCA is widely used in data analysis as it reduces the dimensionality of the dataset, increasing interpretability while simultaneously minimizing the information loss. (Cadima, Principal component analysis: a review and recent developments, 2016)

It can achieve that by defining new uncorrelated variables which maximizes the variance.

These new variables, the principal components, are going to be linear combinations of the previous ones. Identifying such new entities, means solving an eigenvalues/eigenvector problem.

The work *"Principal component analysis: a review and recent developments"* (Cadima, Principal component analysis: a review and recent developments, 2016), gives an extensive overview of the method, its relationship with the Singular Value Decomposition (SVD).

Even though the first documented works related to this approach is from 'On lines and planes of closest fit to systems of points in space' (PRS, 1901), the presence of computers allowed to execute investigations over huge datasets, which was not computationally possible in the first place.

In the common conditions for the use of PCA as tool for data analysis, there are a group of observations on p *numerical* variables, for each of n entities or subjects.

These data quantities define p n-dimensional vectors x_1, ..., x_p or, at the same time, an $n \times p$ data matrix X, whose j_{th} column is the vector x_j of observations on the j_{th} variable. The goal is to find a linear combination of the columns of matrix $\boldsymbol{X}$ characterized by maximum variance.

Those linear combinations are obtained by:

$$\sum_{j=1}^{p} a_{\,j} x_j = \boldsymbol{Xa} \qquad (1)$$

where **a** is a vector of constants $a_1, a_2, \dots, a_p$.

The variance of any such linear combination is obtained by:

$$\mathrm{var}(\mathbf{Xa}) = \mathbf{a'Sa} \qquad (2)$$

where **S** is the sample covariance matrix related with the dataset and ′ represents transpose.

Therefore, identifying the linear combination characterized by maximum variance implies finding a p-dimensional vector **a** which maximizes the quadratic form **a′Sa**.

To be sure to have an exact solution to this problem, an additional constraint must be imposed and the most common one involves collaborating with unit-norm vectors, which is requiring $\mathbf{a'a} = 1$.

The problem is traduced into maximizing:

$$\mathbf{a'Sa} - \lambda(\mathbf{a'a} - 1) \qquad (3)$$

where λ is a Lagrange multiplier.

Differentiating with respect to the vector a, and linking to the null vector, produces the equation:

$$\mathbf{Sa} - \lambda\mathbf{a} = \mathbf{0} \Leftarrow\Rightarrow \mathbf{Sa} = \lambda\mathbf{a} \qquad (4)$$

So, **a** must be a (unit-norm) eigenvector, and λ the related eigenvalue, of the covariance matrix **S**.

The interest is in the largest eigenvalue, λ_1 (and subsequent eigenvector a_1), since the eigenvalues are the variances of the linear combinations defined by the corresponding eigenvector **a**:

$$\mathrm{var}(\mathbf{Xa}) = \mathbf{a'Sa} = \lambda\mathbf{a'a} = \lambda \qquad (5)$$

Equation (4) remains valid if the eigenvectors are multiplied by −1, and so the signs of all loadings (and scores) are uninformed and only their relative magnitudes and sign patterns are important.

It is acknowledged that for any p×p real symmetric matrix, like the covariance matrix **S**, they have exactly p real eigenvalues, λ_k (k = 1, ... , p), and their associated eigenvectors can be discovered to create an orthonormal group of vectors, i.e. $a'_k a_k{}'$=1 if k = k′ and zero otherwise.

A Lagrange multipliers method, with the added limitations of orthogonality of different coefficient vectors, can too be used to demonstrate that the full set of eigenvectors of $\boldsymbol{S}$ are the solutions to the problem of discover up to p new linear combinations $\boldsymbol{X}\boldsymbol{a}_k = \sum_{j=1}^{p} a_{jk}\boldsymbol{x}_j$ which then maximize variance, dependent to uncorrelatedness with earlier linear combinations .

Uncorrelatedness is developed from the fact that the covariance between these two linear combinations, $\boldsymbol{X}\boldsymbol{a}_k$ and $\boldsymbol{X}\boldsymbol{a}_k{}'$, is given by $\boldsymbol{a}'_{k'}\boldsymbol{S}\boldsymbol{a}_k = \lambda_k \boldsymbol{a}'_k \boldsymbol{a}_k = 0 \; if \; k' \neq k$.

It is these linear combinations $\mathbf{X}\boldsymbol{a}_k$ that are called the principal components of the dataset, even though occasionally it is also used the same term when referring to the eigenvectors $\boldsymbol{a}_k$.

In particular, the elements of the eigenvectors $\boldsymbol{a}_k$ are usually called the PC *loadings*, while the components of the linear combinations $\mathbf{X}\boldsymbol{a}_k$ are called the PC *scores*, because they are the values that everyone would score on a given PC.

In the usual approach, it also normal to label PCs as the linear combinations of the centred variables $\boldsymbol{x}_j^*$, with general factor $x_{ij}^* = x_{ij} - \bar{x}_j$, where $\bar{x}_j$ states the mean value of the analysis on variable j.

Such approach does not change the results, since the covariance matrix of a set of centred or uncentered variables is the same, but it has the advantage of providing a direct connection to an alternative, more geometric approach to PCA.

Indicating by $\boldsymbol{X}^*$ the $n \times p$ matrix whose columns are the centred variables $\boldsymbol{x}_j^*$, we have

$$(n-1)\mathbf{S} = \mathbf{X}^{*\prime}\mathbf{X}^*. \qquad (6)$$

Equation 6 connect the eigen-decomposition of the covariance matrix S with the singular value decomposition of the column-centred data matrix $\mathbf{X}^*$.

Whichever random matrix Y of dimension $n \times p$ and rank r (necessarily, $r \leq \min\{n, p\}$) can be written as

$$\mathbf{Y} = \mathbf{ULA}' \qquad (7)$$

where U, A are $n \times r$ and $p \times r$ matrices with orthonormal columns ($U'U = I_r = A'A$, with I_r the $r \times r$ identity matrix) and L is an $r \times r$ diagonal matrix.

The columns of **A** are called the *right singular vectors* of **Y** and are the eigenvectors of the $p \times p$ matrix $\mathbf{Y'Y}$ associated with its non-zero eigenvalues.

The columns of **U** are called the *left singular vectors* of **Y** and are the eigenvectors of the $n \times n$ matrix $\mathbf{YY'}$ that stand for its non-zero eigenvalues.

The diagonal elements of matrix L are called the *singular values* of **Y** and are the non-negative square roots of the (common) nonzero eigenvalues of both matrix $\mathbf{Y'Y}$ and matrix $\mathbf{YY'}$.

It is assumed that the diagonal elements of **L** are in decreasing order, and this uniquely states the order of the columns of **U** and **A**.

Therefore, taking $\boldsymbol{Y} = \boldsymbol{X}*$, the right singular vectors of the column-centred data matrix $\boldsymbol{X}*$ are the vectors $\boldsymbol{a}_k$ of PC loadings.

Due to the orthogonality of the columns of A, the columns of the matrix product **X*A=ULA′A=UL** are the PCs of **X***.

The variances of these PCs are obtained from the squares of the singular values of **X***, divided by n – 1.

In addition, and given Equation 6 and the properties above,

$$\mathbf{(n-1)S=X^{*\prime}X^{*}=(ULA^{\prime})^{\prime}(ULA^{\prime})=ALU^{\prime}ULA^{\prime}=AL^{2}A^{\prime}} \quad (8)$$

where $\mathbf{L}^2$ is the diagonal matrix with the squared singular values (i.e. the eigenvalues of (n−1)S).

Equation 8 gives the *spectral decomposition*, or *eigendecomposition*, of matrix (n− 1)S.

Consequently, PCA is equivalent to an SVD of the column-centred data matrix **X***.

The properties of an SVD imply interesting geometric interpretations of a PCA.

Assumed any rank r matrix **Y** of size $n \times p$, the matrix $\mathbf{Y}_q$ of the same size, but of rank q<r, whose elements minimize the sum of squared differences with related elements of **Y** is obtained from:

$$\boldsymbol{Y}_q = \boldsymbol{U}_q \, \boldsymbol{L}_q \, \boldsymbol{A}'_q \quad (9)$$

where $\boldsymbol{L}_q$ is the $q \times q$ diagonal matrix with the first (largest) q diagonal elements of **L** and $\boldsymbol{U}_q$, $\boldsymbol{A}_q$ are the $n \times q$ and $p \times q$ matrices found by saving the q corresponding columns in **U** and **A**.

For example, the n rows of a rank r column-centred data matrix **X*** identify a scatterplot of n points in an r-dimensional subspace of $\mathbb{R}^p$, with the origin as the centre of gravity of the scatterplot.

That result indicates that the 'best' n-point approximation to this scatterplot, in a q-dimensional subspace, is obtained from the rows of $\boldsymbol{X}_q^*$, defined as in Equation 9, where 'best' means that the sum of squared distances between relating points in each scatterplot is minimized, as in the original approach by Pearson (PRS, 1901).

The system of q axes in this exemplification is given by the first q PCs and defines a *principal subspace.*

Therefore, PCA is at heart a dimensionality reduction technique, where a set of p original variables can be replaced by an optimal set of q derived variables, the PCs.

When q =2or q = 3, a graphical approximation of the n-point scatterplot is possible and is often used for an initial visual portrayal of the full dataset.

It is important to remark that this result is incremental (hence adaptive) in its dimensions, meaning that the best subspace of dimension $q + 1$ is achieved by adding a further column of coordinates to those that defined the best q-dimensional solution.

The quality of any q-dimensional approximation can be determined by the variability connected with the set of retained PCs.

The sum of variances of the p original variables is the trace (sum of diagonal elements) of the covariance matrix **S**.

Simple matrix theory results can be used to show that this value is also the sum of the variances of all p PCs.

Then, the ordinary measure of quality of a given PC is the proportion of total variance that it accounts for

$$\pi_j = \frac{\lambda_j}{\sum_{j=1}^{p} \lambda_j} = \frac{\lambda_j}{tr(\boldsymbol{S})} \tag{10}$$

where tr(S) denotes the trace of S.

The incremental nature of PCs also implies that we can use a proportion of total variance described by a set S of PCs (usually, the first q PCs), which is often expressed as a *percentage* of total variance accounted for: $\sum_{j \epsilon s} \pi_j \times 100\%$.

It is most common to use a particular pre-defined value of cumulative variance to choose how many PCs should be taken, even though the conditions of graphical representation occasionally led to the use of just the first two or three PCs.

Even in such situations, the percentage of total variance described for is a vital tool to assess the quality of these low-dimensional graphical representations of the dataset.

The highlighting in PCA is always on the first few PCs, but there are circumstances in which the last few may be of interest, such as the project described in this paper in which each one of them may have a specific role in the motion planning process.

3.3. Analysis performed per specific objective

The eight joints under investigation were:

- Thorax flexion/extension -(q0)
- Shoulder plane of elevation -(q1),
- Shoulder elevation angle -(q2),
- Shoulder axial rotation -(q3).
- Elbow: flexion/extension -(q4)
- Elbow pronation/supination (i.e., axial rotation of the forearm— q5).
- Wrist flexion/extension -(q6)
- Wrist ulnar/radial deviation -(q7).

As shown in Figures 3 and 4.

The input information was in the form of time-sampled evolution of those eight angles, with a sampling frequency of 100 Hz, describing each one of the six motor skills, computed by the sixteen different individuals.

The data were organised in the form of a *n*x8 matrix per each tester's motor skill, where *n* was the number of time samples.

The matrices considered all the eight repetitions that each user made per each task.

Given this kind of input to be investigated, to be able to identify the kinematic synergies in those activities and study them, the analysis was made using MATLAB (the MathWorks, Natich, MA, USA).

In this work we used the following function:

[*coeff*, *score*, *latent*, *tsquared*, *explained*] = pca(*data*);

As '*data*', was the input dataset, different values could be obtained:

- '*coeff*':
  This matrix contains the principal component coefficients.
  Each column corresponds to a principal component, and each row corresponds to a joint angle.

- '*score*':
  This matrix contains the scores of each time sample along the principal components. It represents the data in the reduced-dimensional space.

- '*latent*':
  This vector contains the eigenvalues of the covariance matrix, which represent the explained variance of each principal component.

- '*tsquared*':
  This is a matrix containing the Hotelling's T-squared statistic, which is used for outlier detection.

- '*explained*':
  This vector contains the percentage of total variance explained by each principal component.

This function, with its results, was essential to address all the specific objectives of the project. The next paragraphs are going to be dedicated to the description of each one of them.

3.3.1. How many synergies are needed to describe the data?

To answer that specific question, the investigation performed on MATLAB addressed the value of variance covered by the synergies.

As mentioned in the theoretical description of the PCA, it is common to study those values to be able to suggest how many PCs can be used to describe the original data.

The specific threshold of the variance is up to the researcher, but a quantity like 85/90% of it could be the right choice to represent the input, as seen in literature.

The development of the angles, which was covered by each synergy, was present in the '*explained*' vector obtained using the MATLAB function.

Assessing how much was the cumulative variance for the principal components, was the step made in choosing how many of them were going to be used.

3.3.2. How were characterized those synergies in terms of their relationship with the joints?

Once the number of synergies was selected, and the PCA analysis was performed, the function returned a series of coefficients which were useful to identify the properties of the PCs.

Noteworthy, the relationship between the synergies and the joints was investigated, to be able to know how those hidden pseudo-movements were characterized.

As previously mentioned, inside this objective there were some specific features that were tried to be assessed:

1. Which joints were the most influential in each synergy;
2. Which joints were more correlated with the synergy;
3. Which joints were coordinated in their changes during the pseudo-movement made by the synergy.

For the investigation regarding the more influential joints for each synergy, the key to solving that problem was using the '*coeff*' variable.

This quantity was an eight-by-eight matrix, as there were eight columns regarding the possibles principal components and eight row for the joints. Each cell described how much each angle influenced each synergy. Extracting the values for the components selected and sorting them in descending order showed which joints were more influential in the pseudo-movements.

To assess which joints were the most relevant, it was chosen a threshold of 0.2 for the value.

The next step was analysing the correlation between the different joints and each synergy.

This investigation shows the strength and the direction of the linear relationship between the angles and the pseudo-movement beneath the task analysed. This evaluation was done by calculating the Pearson coefficient between the joints and the synergies, using a MATLAB function called: ‘ *corr (…)* ‘. The results show the relationship between their directions in the movement, without a temporal aspect.

The last step, instead, provided the description of the time connection between the synergy and the joints, studying their ‘*phase relationship*’.

This investigation assessed the way the angles and the principal component were moving, describing their temporal coordination. It allowed to see if the joints consistently lag or lead in their progress compared to the synergy. This analysis was performed using a cross-correlation technique, showing the synchronization between the entities in the data, thanks to a simple MATLAB function called: ‘*xcorr(…)*’.

All these three specific sub-studies provided an overall description of the synergies and the relationship between them and the angle joints.

3.3.3. How much of the overall movement per joint did each synergy cover?

Once these steps were completed, the attention shifted to the study of the overall movement produced by the synergies. This analysis was intended to assess how much of the overall movement made by each joint was describing each synergy.

This investigation wanted to see if a specific synergy was responsible for the overall movement made by an angle, such that using the principal component to recreate the trajectory would return the same changes in that joint.

To do that, a new entity called ‘*synthetic-movement*’ was defined. This new variable, which was generated from the principal components extracted from the data, could be seen as the idealised representation of a joint’s movement pattern based on that synergy alone.

Using those ‘*synthetic movements*’ and studying their value of variance about one of the overall movements made by the related joint was a good approach to see how much of the overall changes they covered.

This idealised development made by the synergies was obtained by managing the ‘*scores*’ and ‘*coeff* ’ variables. Multiplying the ‘*score*’ for that principal component, with the ‘*coeff*’ value for the specific joint, created the ‘*synthetic movement*’ for those two entities, which represented the movement the angle would made only because of that specific synergy.

3.3.4. Reconstruction of the trajectory and comparison

Once each principal component's contribution to the joints' movement was assessed, it was possible to pass to the last step of the research. The final analysis regarded the reconstruction of the trajectories of the end effector. The goal of this investigation was to check how close was the reconstructed version, to the original one, which would then imply that the kinematic synergies could be used for the motion planning of the exoskeleton.

To achieve this step, it was necessary to develop a MATLAB code that could not be obtained using an intrinsic function of the software. The program creates a simulated arm, composed of shoulder, elbow, and wrist, that was going to change its configuration given the input angles that were provided.

Because of that, a first execution of the code was made to evaluate the trajectory computed by the end effector during the experiments, as the input data to the program were the original values of the eight angles.

Once this step was done, this procedure was going to be repeated with the reconstructed quantities obtained after doing the PCA analysis. Choosing a specific number of kinematic synergies, it was possible to obtain rebuilt values of the angles, thanks to the use of the 'synthetic movements'.

The measures of the eight joints derived from those 'hypothetical actions' were then provided to the software as new input data, to create the reconstructed trajectory of the end effector based on the kinematic synergies.

This operation was repeated for all the motor skills computed by each individual and the path shown from the figures, described all the eight repetitions of such tasks made by the users.

The quality of the reconstruction was assessed using the RMSE (Root Mean Square Error), which is a measure of the average magnitude of the errors between reconstructed and original values, in cm.

4 Results

This chapter is appointed for the description of the results obtained from each one of the specific analyses preformed.

4.1. Number of synergies identified

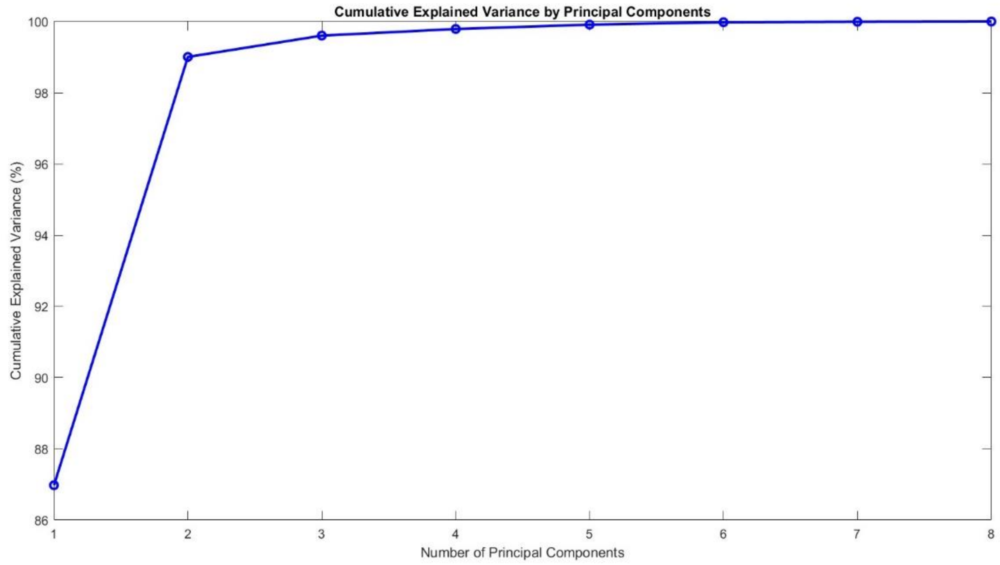


Figure 7: Example of number of synergies identified for individual one motor skill one

The first step was identifying the kinematic synergies in the data, focusing on the percentage of variance each one of them covered. This analysis, as mentioned before, was done individually per each user's motor skill.

As it can be seen for the example shown in Figure 8, which regarded individual one motor skill one, the number of synergies needed to cover a reasonable percentage of the variance of the data (which is of 90%) is between one and two principal components.

As mentioned in the description of the experimental procedure, the motor skills were the following:

1) Anterior reaching at rest position height (ARR)

2) Anterior reaching at shoulder height (ARS)

3) Hand to mouth with object (HMO)

4) Hand to mouth without object (HMX)

5) Move objects at rest position height (MOR)

6) Move objects at shoulder height (MOS)

Once repeated for all the user's motor skills, it can be observed that this value is the same for each one of them, even though on some occasions it can grow to three or four.

The number of synergies necessary to cover the 90% of variance in the data for each operator's motor skills is shown in Table 4.

	Motor skill one (ARR)	Motor skill two (ARS)	Motor skill three (HMO)	Motor skill four (HMX)	Motor skill five (MOR)	Motor skill six (MOS)
User 1	86,98	88,69	80,29	99,42	69,43	73,79
User 2	90,21	85,23	83,80	96,72	74,98	86,78
User 3	92,98	91,41	80,52	86,62	53,98	70,41
User 4	91,25	90,34	65,90	99,51	82,35	85,15
User 5	87,62	88,27	86,49	98,76	59,15	69,11
User 6	89,96	89,16	59,87	97,48	69,57	73,58
User 7	94,24	93,83	54,15	98,55	80,83	87,13
User 8	-	62,35	74,70	97,99	66,43	80,03
User 9	95,07	89,86	84,33	99,41	79,72	81,80
User 10	80,93	80,40	92,51	98,93	45,04	46,52
User 11	88,45	74,18	45,75	83,28	53,74	78,70
User 12	92,75	92,28	73,02	99,19	71,62	88,86
User 13	70,00	82,12	45,27	77,49	63,77	59,72
User 14	94,63	86,89	64,50	98,95	78,59	-
User 15	47,86	76,43	82,77	54,33	74,93	55,83
User 16	55,22	82,38	-	70,25	67,73	51,44

Table 4: Percentage of variance covered by the first P.C.

	Motor skill one (ARR)	Motor skill two (ARS)	Motor skill three (HMO)	Motor skill four (HMX)	Motor skill five (MOR)	Motor skill six (MOS)
User 1	2	2	2	1	2	2
User 2	1	2	2	1	3	2
User 3	1	1	2	2	3	3
User 4	1	1	3	1	2	2
User 5	2	2	2	1	2	3
User 6	2	2	3	1	2	3
User 7	1	1	2	1	2	2
User 8		2	2	1	3	3
User 9	1	2	2	1	2	2
User 10	2	2	1	1	3	3
User 11	2	2	2	2	3	2
User 12	1	1	2	1	2	2
User 13	3	2	3	2	3	3
User 14	1	2	3	1	2	
User 15	4	3	2	3	3	3
User 16	3	2		2	3	3

Table 5: Number of principal components necessary to cover 90% of the variance of the data.

In some cases, there were some missing data in the input data obtained from the previous work, which could not be fixed, so the cells are empty.

4.2. Exemplative results on a pilot user/task

The next step assessed the properties of each of the derived synergies, to have a better understanding of their characteristics and their relationships with each one of the joint angles.

As previously introduced, the analysis was performed individually per each user's motor skill. The results shown in this section considered the motor skill number three (Hand to mouth with object) for user number two.

As the task number three makes the easiest movement among all, and it is therefore a good choice for pilot showing the results. In this case, the synergies needed to cover the 90% of the variance were two. The deep dive investigation is repeated for each one of two synergies.

4.2.1. Synergy one (for individual two's motor skill three)

This section describes the adopted approach showing the results obtained for the first synergy, identified for individual two's motor skill three.

As mentioned in the specific objectives, the first kind of analysis performed regarded the importance of the different angles inside each synergy. As it can be observed from Figure 9, which shows the values returned from the investigation about operator one's motor skill one, the more influential joint over the movement is:

- Forearm pronation/supination -(q5)

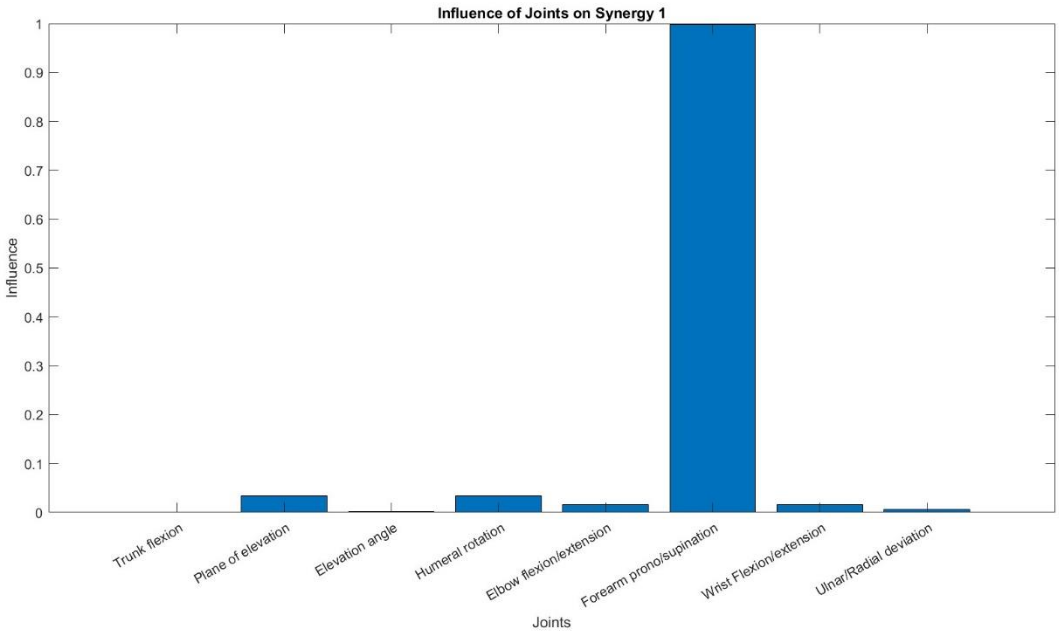


Figure 8: Influence of joints with synergy one

This means that q5 is the angle changing the most during the pseudo-movement made by the synergy, in this case.

Once this interesting feature was individuated, the analysis shifted to observe which joints were more correlated with the principal component, so which ones had the strongest linear relationship and in which direction was it.

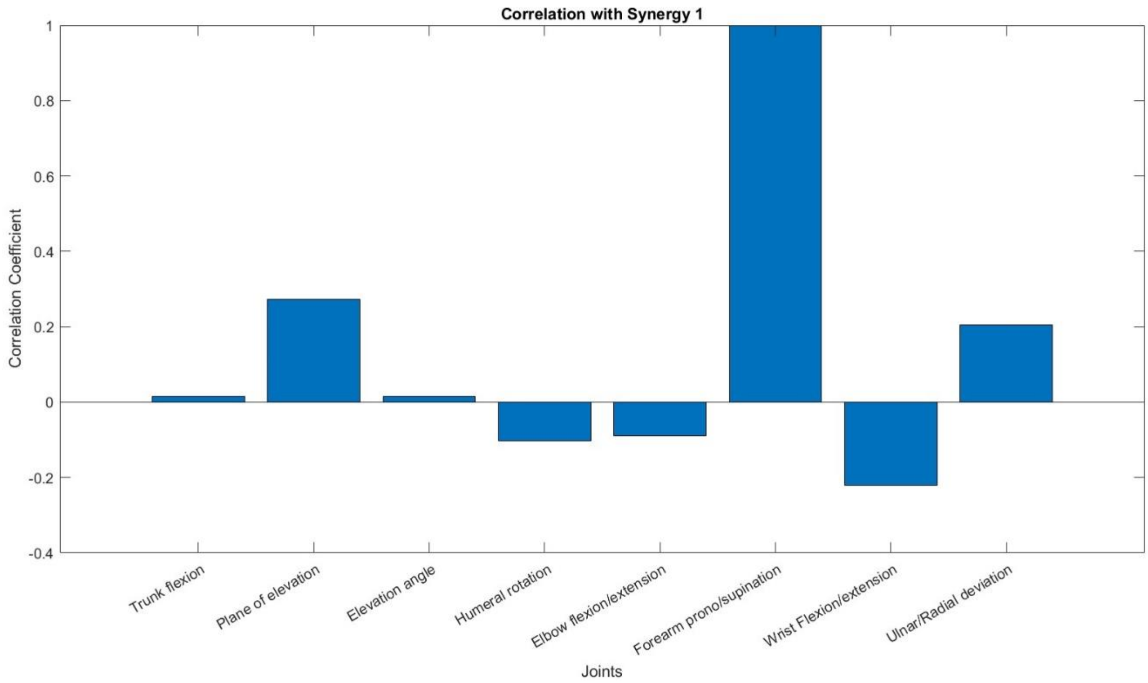


Figure 9: Correlation of joints with synergy one

As it can clearly see from Figure 10, some joints have a positive linear relationship with the synergy, so are moving in the same direction, while others do not. This is an interesting side of their connection to be observed, to understand how it is characterised the pseudo-movement made by that principal component.

As for this first example, the analysis allowed to observe that:

- Forearm prono/supination is the joint moving the most inside the most important synergy for individual two's motor skill three, as it is the only angle above the threshold value of 0.2.

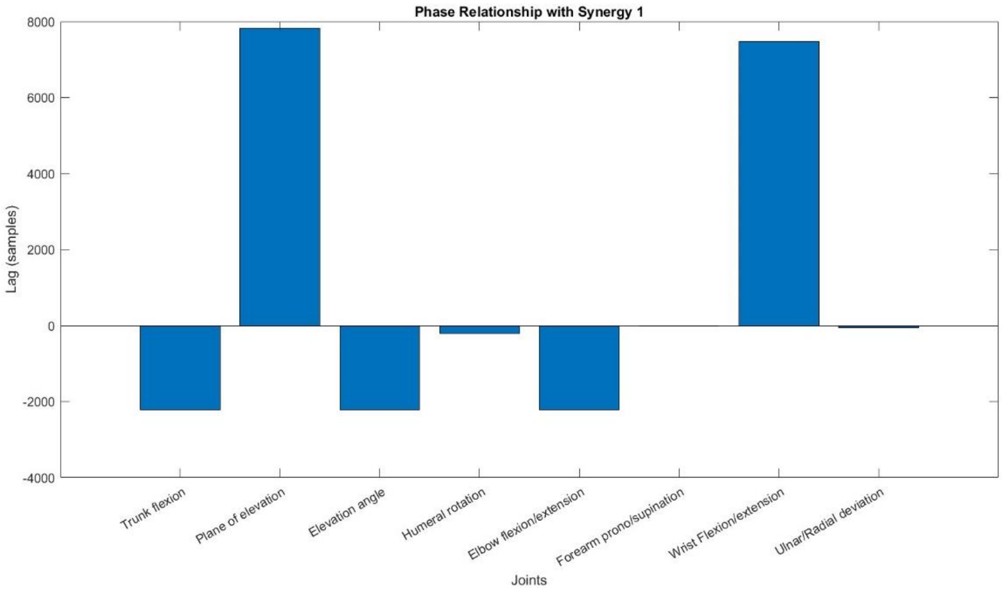


Figure 10: Phase relationship with synergy one

At the same time:

- Shoulder plane of elevation -(q1), Forearm pronation/supination -(q5), Wrist ulnar/radial deviation -(q7); moves in the same direction as the pseudo-movement made by the synergy
- Shoulder axial rotation -(q3), Elbow: flexion/extension -(q4), Elbow pronation/supination (i.e., axial rotation of the forearm— q5), moves in the opposite direction, even with different intensity.

The final investigation performed regarded the temporal connection between the joint angles and the synergy – are they moving in the same direction? Are they synchronized or is there a time shift between their movements?

As it can be seen from Figure 11, the joints are not in phase with the movement of the synergy. Joint two and seven, instead, have a considerable time advance and the other joints have little time lag.

4.2.2. Synergy two (for individual two's motor skill three)

Those three analyses regarding the properties of the synergies, were repeated for the second one, which made possible to cover at least the 90% of the variance of the original data.

As previously described, the first step was studying the most influential joints in the principal components, to see which angles moved the most.

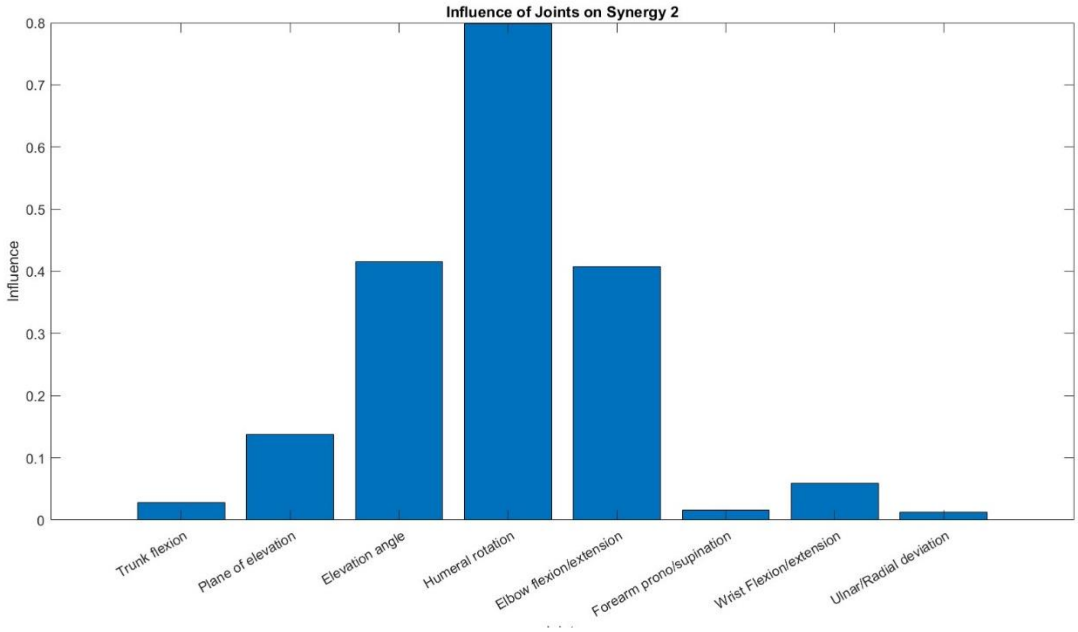


Figure 11: Influence of joints for synergy two

As it can be observed from Figure 12, this time the most significant angles were Elevation angle (q2), Humeral rotation (q3) and Elbow flexion/extension (q4).

The next step performed regarded the correlation between the joints and the synergy.

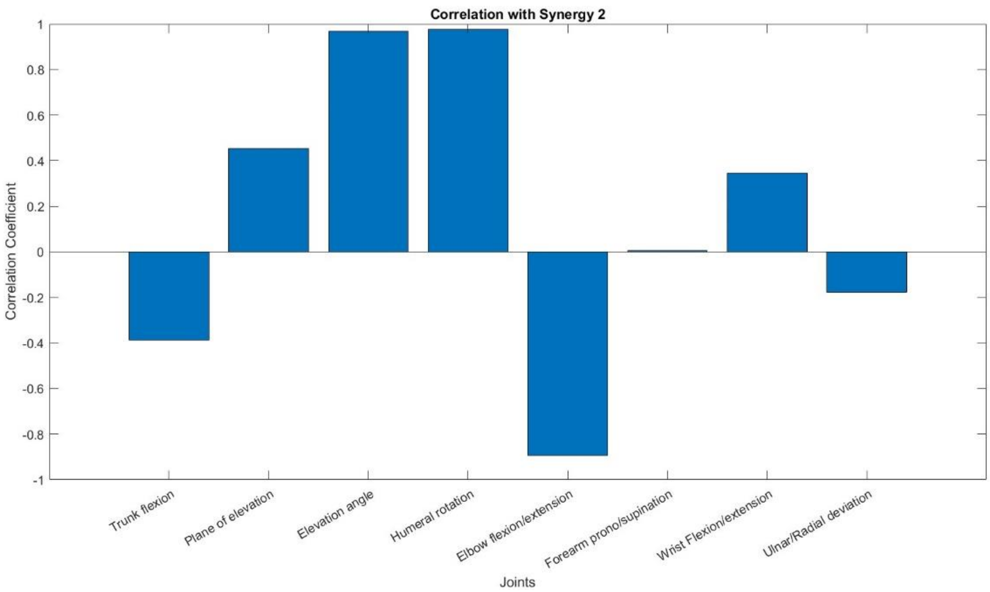


Figure 12: Correlation of joints with synergy two

As it can be seen from Figure 13, in this synergy the linear relationship is most of the time positive, so the joints change in the same direction of the synergy, besides the last one.

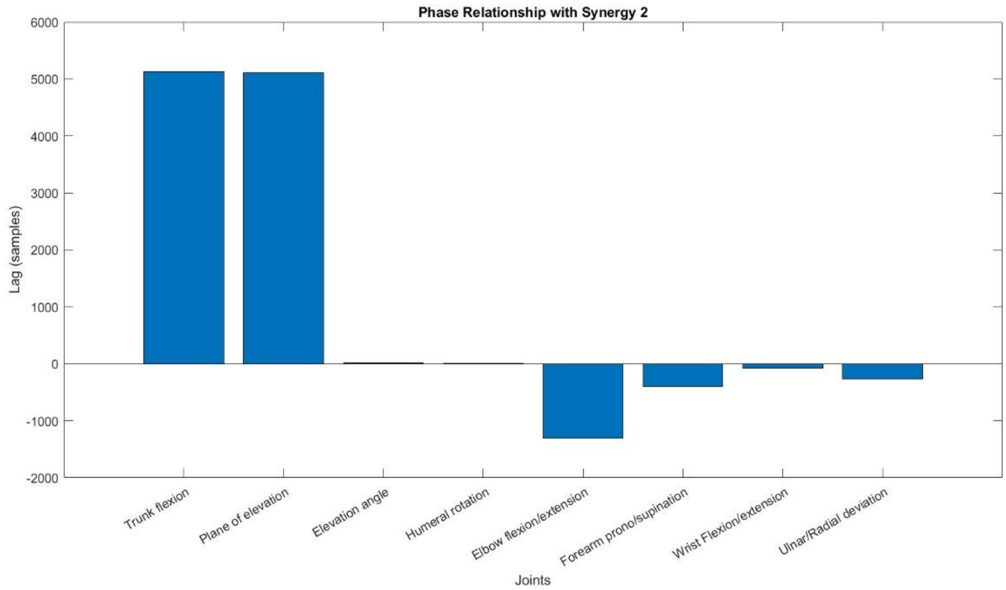


Figure 13: Phase relationship with synergy two

The final analysis performed was about the temporal connection in the modifications, between the angles and the principal component. As it can be observed from Figure 14, this synergy is characterised by a very specific synchronization between its joint. Joint one and two, have a considerable time advance, while the other have a little time delay.

It can be observed in particular for what regards the joints moving the most that the two synergies has a sort of complementary connection: as the first PCA moved the most in Forearm pronation/supination -(q5), the second PCA changes the most in shoulder elevation angle –(q2), Shoulder axial rotation -(q3), Elbow: flexion/extension -(q4). This confirms the hypothesis of the complementary aspect of the synergies.

They represent different pseudo-movements which execute the motor skill. The subsequent step examined was the quantity of the overall movement made by each joint, covered by each synergy.

This investigation returned an essential information, as the goal was to verify if the principal component comprehended the overall movement made by the user, so that reconstructing the trajectory by using the synergy alone, would return an acceptable end effector position.

As mentioned before, this analysis was performed for individual two's motor skill three thanks to use of '*synthetic-movements*'.

4.2.3. Variance covered by synergy one

Those idealized movements, which were compared on their variance to the original ones, showed that the first synergy covered most of the changes made by:

- forearm pronation/supination joint,

as it can be seen from Figure 15.

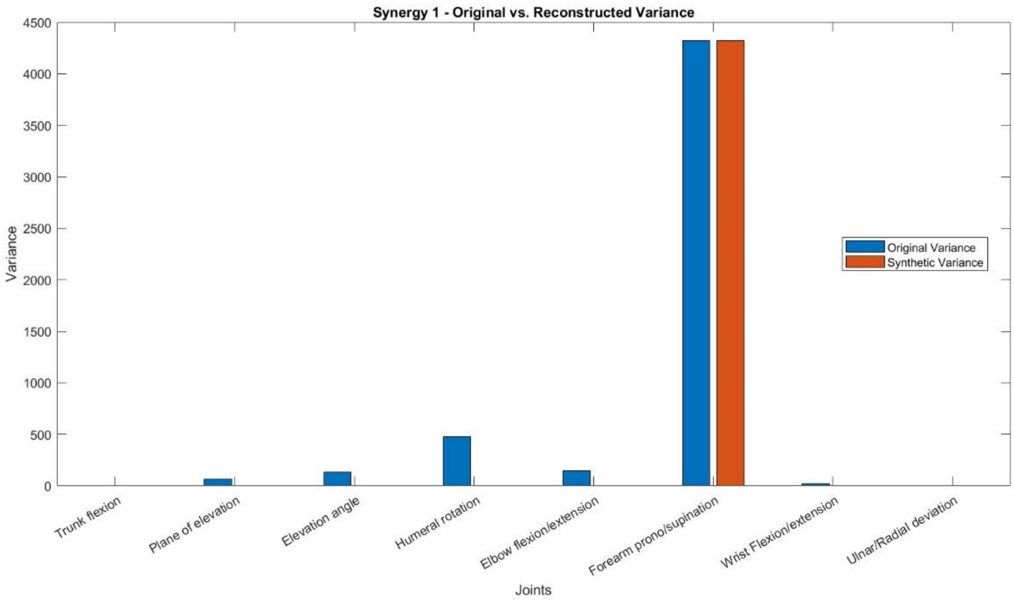


Figure 14: Original and reconstructed variance for synergy one

In detail, Figure 16, show the percentage of the original variance per each joint covered by the first synergy.

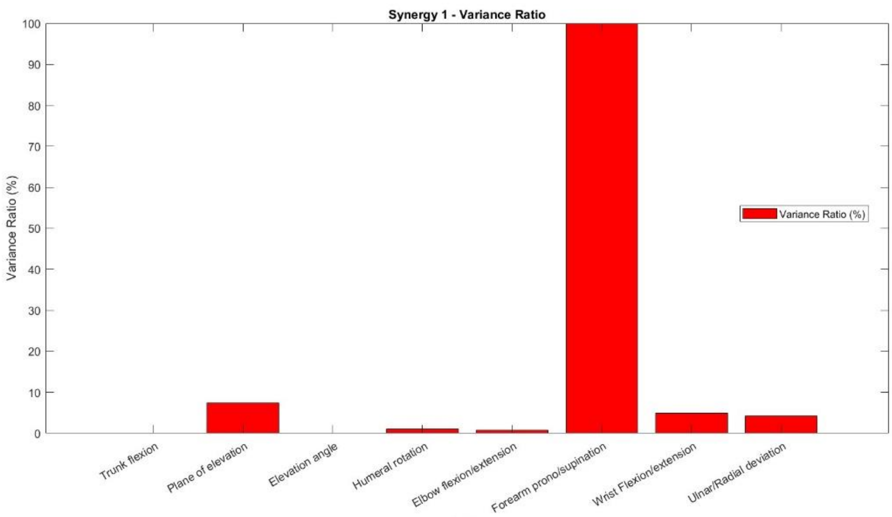


Figure 15: Variance ratio for synergy one

The results confirmed the fact that using this synergy to reconstruct the trajectory would cover almost all the changes made by Forearm pronation-supination.

4.2.4. Variance covered by synergy two

Repeating the analysis for the second synergy returned a notable view of the situation and their difference. It can be observed from Figure 17 and Figure 18 that this principal component contributed significantly to the movement of joint three, four and five, covering a huge amount of their variance.

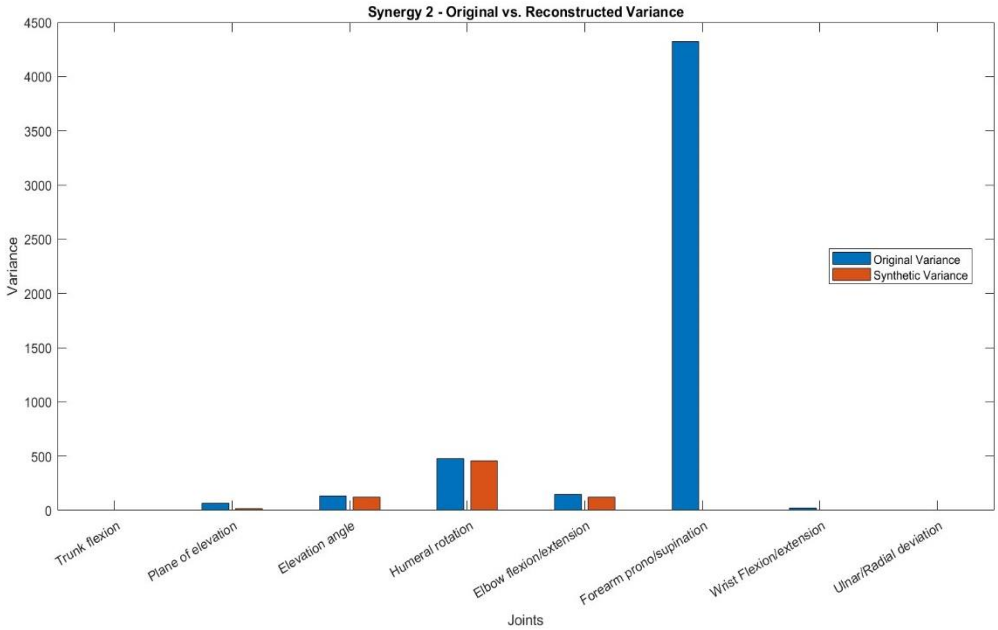


Figure 16: Original and reconstructed variance for synergy two

The comparison of this result with the precedent one, showed that the two synergies are complementary in covering the overall movement of user while he is achieving the motor skill number three.

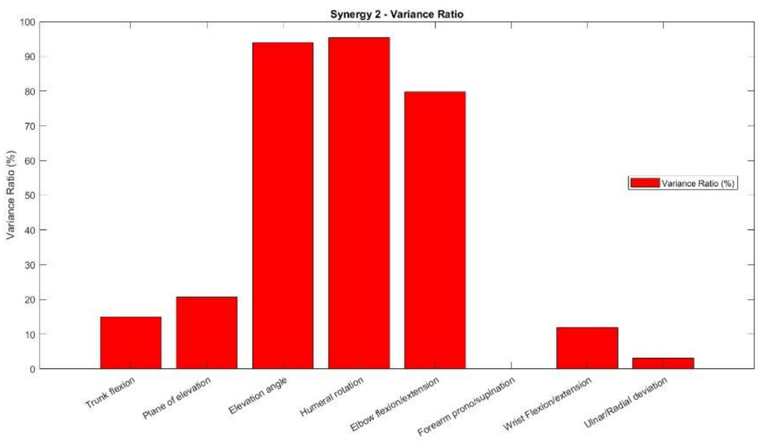


Figure 17: Variance ratio for synergy two

4.2.5. Trajectory reconstruction

This section is going to show the results obtained for the trajectory reconstruction using the synergies, and the comparison with the original one. Here we show the detailed results of each methodological step on an exemplificative user (2) and exemplificative task (HMO).

To be able to visualize the path made by the end effector, a MATLAB code was created. That code created a simulated structure of the arm, which changed its configuration and position given the input angles.

As it can be observed from Figure 19, the initial position and orientation of the arm was straight in from of the user with elbow, shoulder and wrist aligned (the wrist is characterized by the blue and red axes).

Starting from such initial point, the time sampled evolution of the initial angles was provided (Figure 20), so that the arm could move and perform the original trajectory.

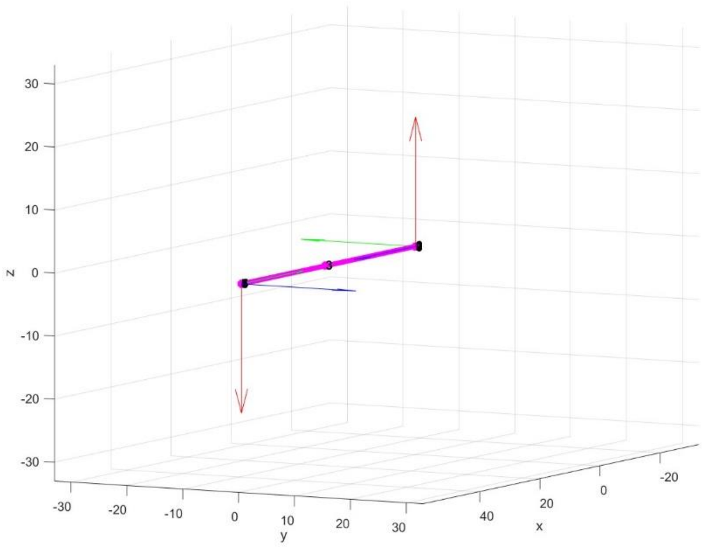


Figure 18: Initial configuration of the arm

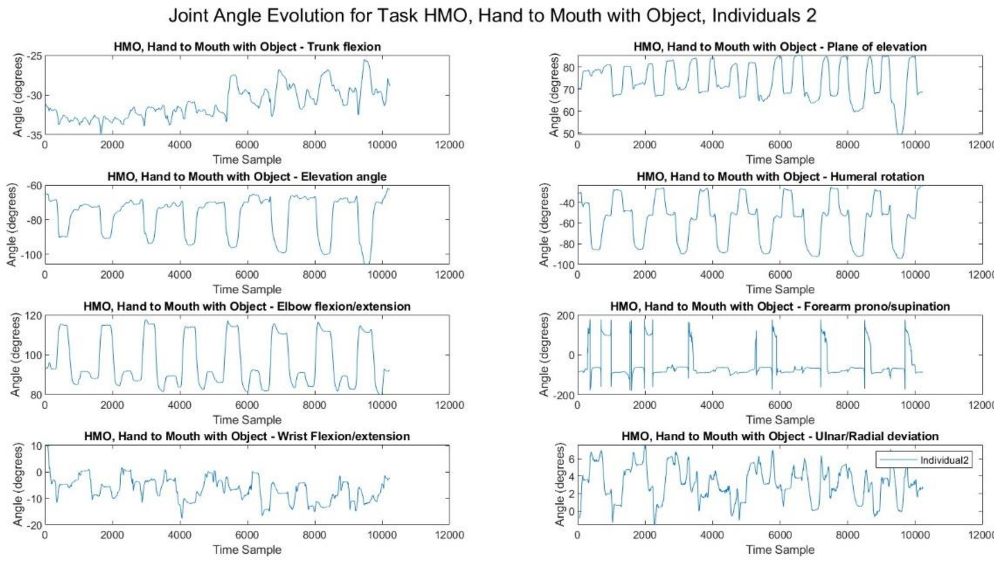


Figure 19: Original angles' profile

It must be considered that the first angle, trunk flexion, was neglected in the computation of the path, since it has been shown to have very little effect on the movement. This was anyway expected, since during data acquisition subjects were asked not to move the trunk.

Once the position of the end effector was calculated and updated for each one of the time samples, it was possible to derive the trajectory executed by the end effector in during the execution of the motor skill.

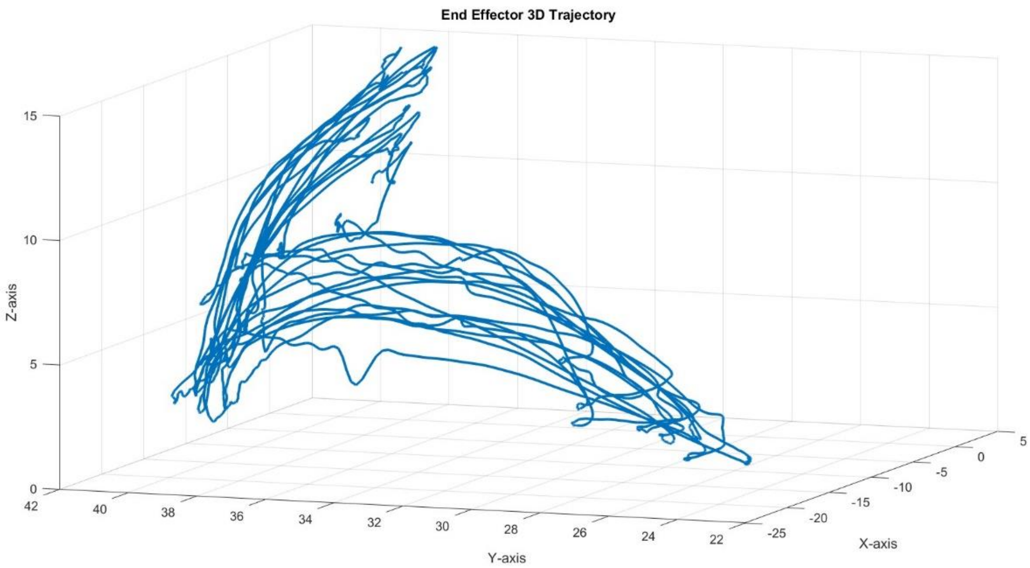


Figure 20: Original trajectory of the EE of HMO by Individual 2

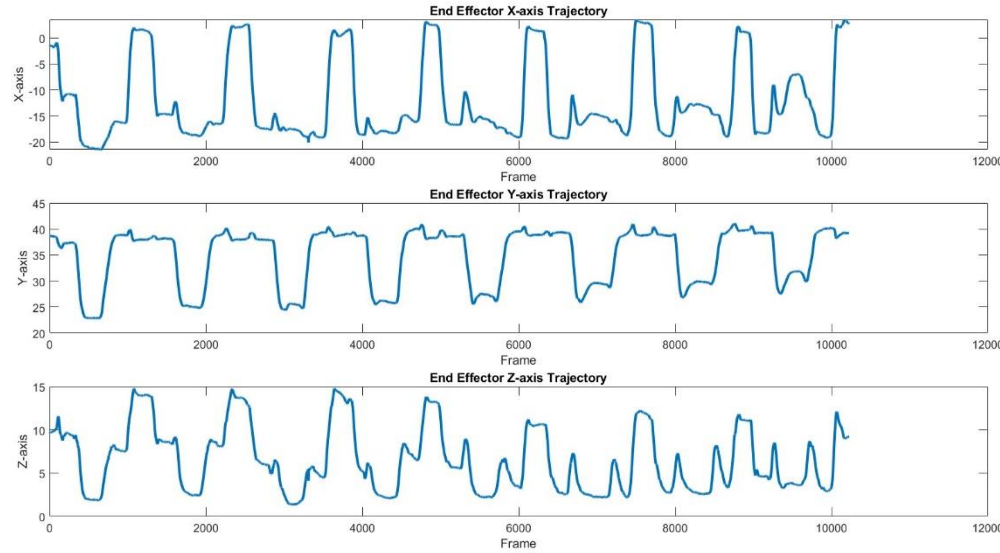


Figure 22: Original trajectory profile dimension per dimension

Observing Figure 21 and Figure 22, it is possible to observe the movements of end effector, in a motor skill in which was required to take an object and bring it to the mouth. It is in such form because it represents the whole eight repetitions of the task which each tester was requested to do.

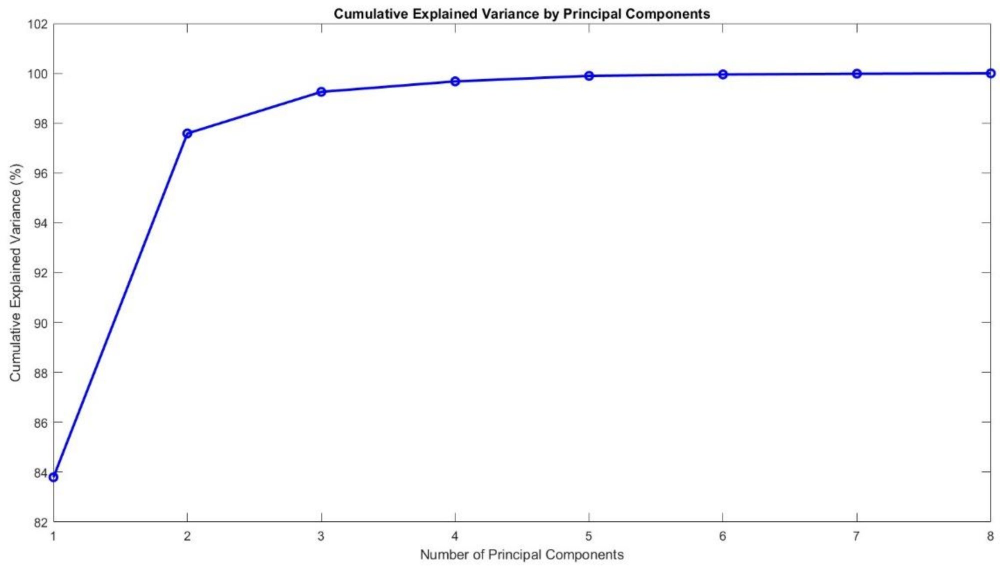


Figure 22: PCA analysis and cumulative variance for HMO performed by individual 2

After observing the original trajectory computed by individual two, it was then the time to reconstruct it using the kinematic synergies which were identified using the 'Principal components analysis'.

PCA discovered the patterns in the time sampled evolution of the angles, and used the principal components of choice, to reconstruct the original dataset using the synthetic movements.

Once the profile of the eight joints was rebuilt, it was provided as input to the 'trajectory computation' code, to be able to see how accurate was in comparison to the original one.

This step was performed choosing different number of principal components, covering different percentages of variance of the angle's dataset, to observe how did the situation change in each circumstance.

4.2.6. Reconstruction using one principal component

The first step executed is going to assess the quality of the reconstruction using one principal component and then increase the number of PCAs to see how would the results improve.

The first principal component of this example covered the 84% of the variance of the data, which was not above the threshold of 90%.

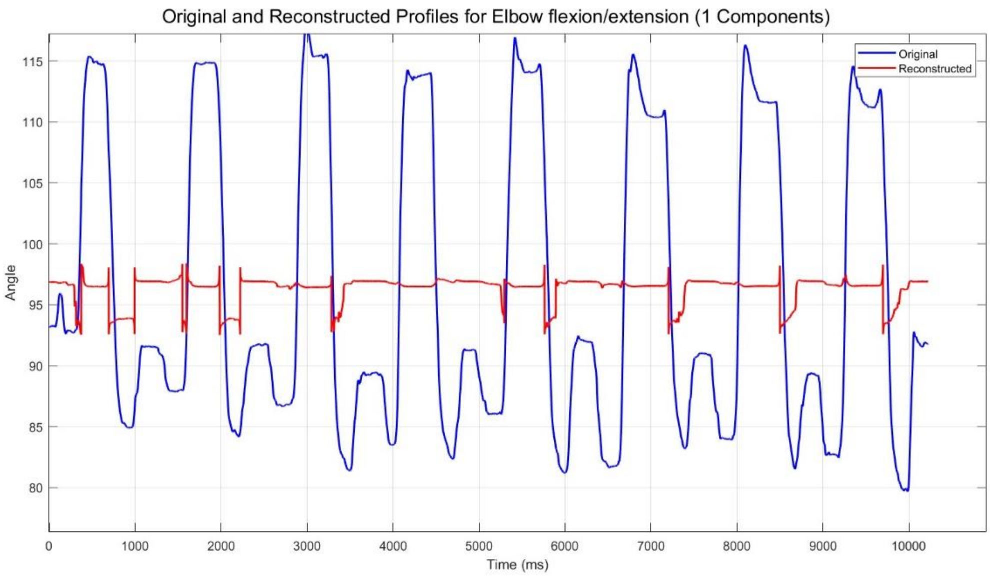


Figure 23: : Reconstruction of Elbow flexion/extension using one component

As it can clearly see from the Figure 24 the reconstruction is not accurate at all, which can also be seen on the trajectory, in Figure 25.

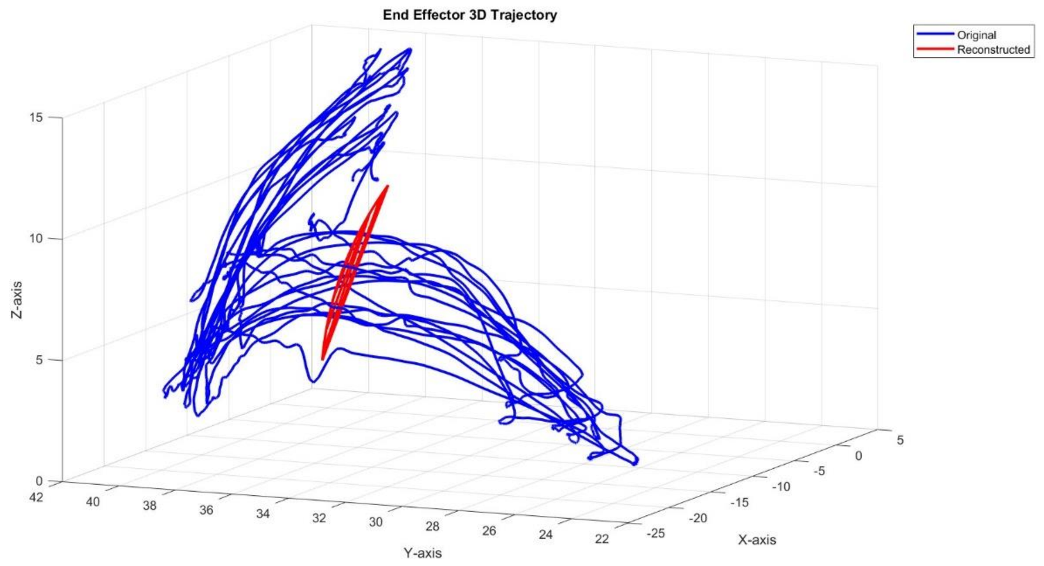


Figure 24: 3D trajectory reconstruction using one component

The results clearly indicate the necessity of increasing the number of principal components for the reconstruction.

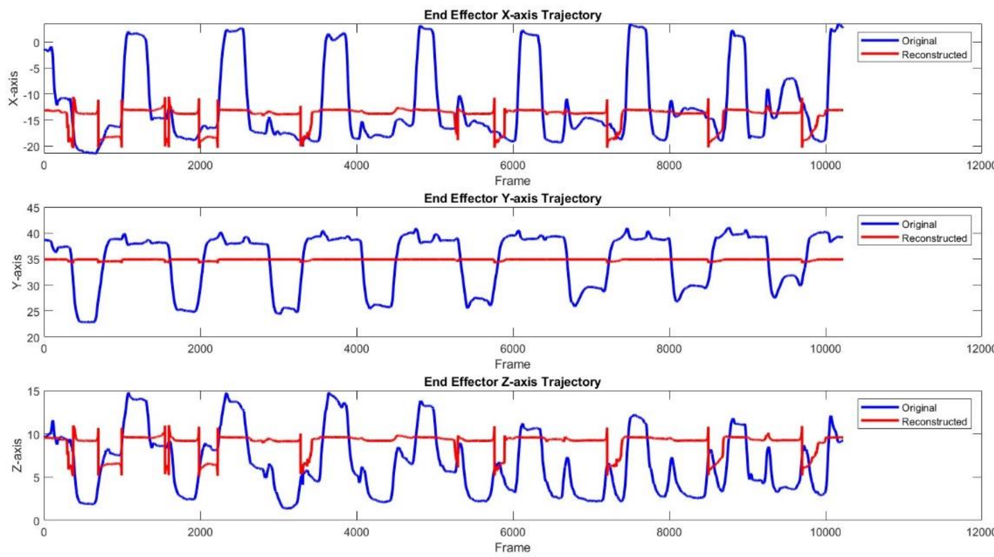


Figure 25: Dimension per dimension trajectory reconstruction using one component

4.2.7. Reconstruction using two kinematic synergies

The second step executed was choosing two principal components for the reconstruction, as they covered the 97% of the variance of the dataset as it can be seen from Figure 23.

As initial phase, it was observed how accurate was the reconstruction on a single angle from the original dataset, specifically it was chosen to check 'Elbow flexion-extension.'

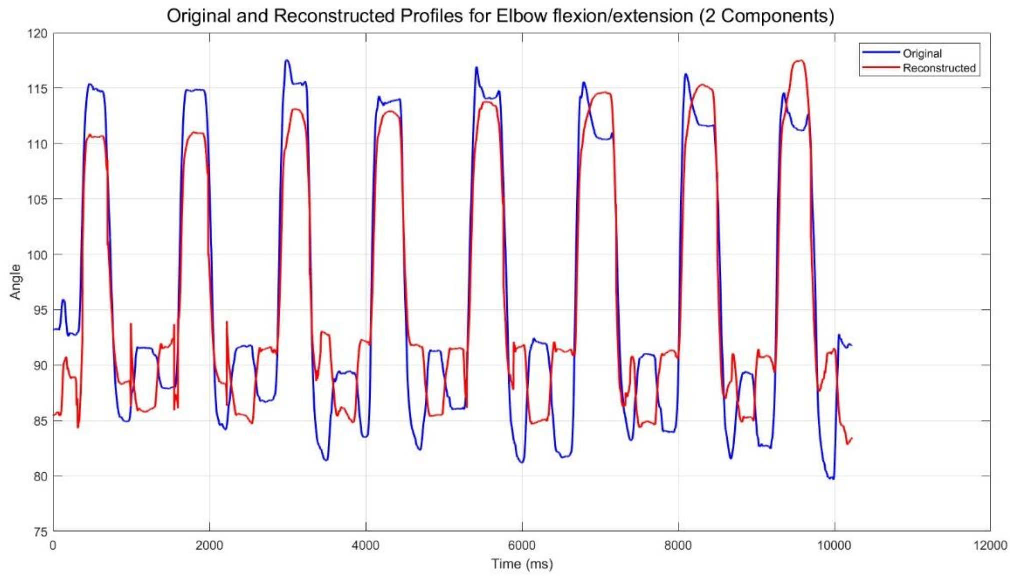


Figure 26: Reconstruction of Elbow flexion/extension using two components

It can be noticed from Figure 27 that it resembles the shape of the behavior, but it is not fully accurate.

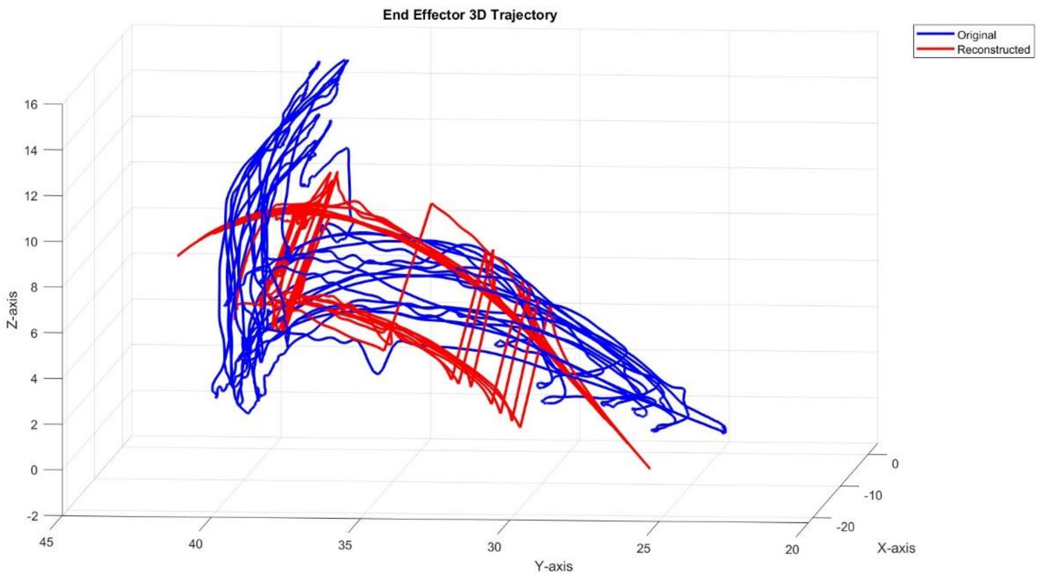


Figure 27: Trajectory reconstruction using two components

Following that, all the reconstructed angles were used to generate the new trajectory.

Even though it may be alike to the original one on the Y-axis, it can be noted from Figure 28 and 29, that the two trajectories are not similar, which means that it is necessary to increment the number of principal components used.

Additional assessment on the quality of the reconstruction is provided from the value of RMSE, showed in Figure 30.

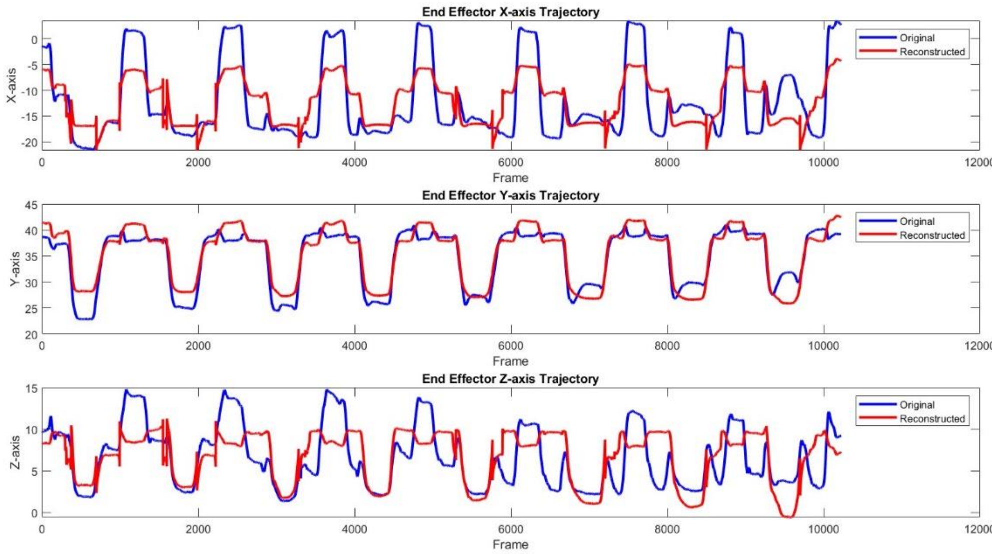


Figure 28: Dimension per dimension trajectory reconstruction using two components

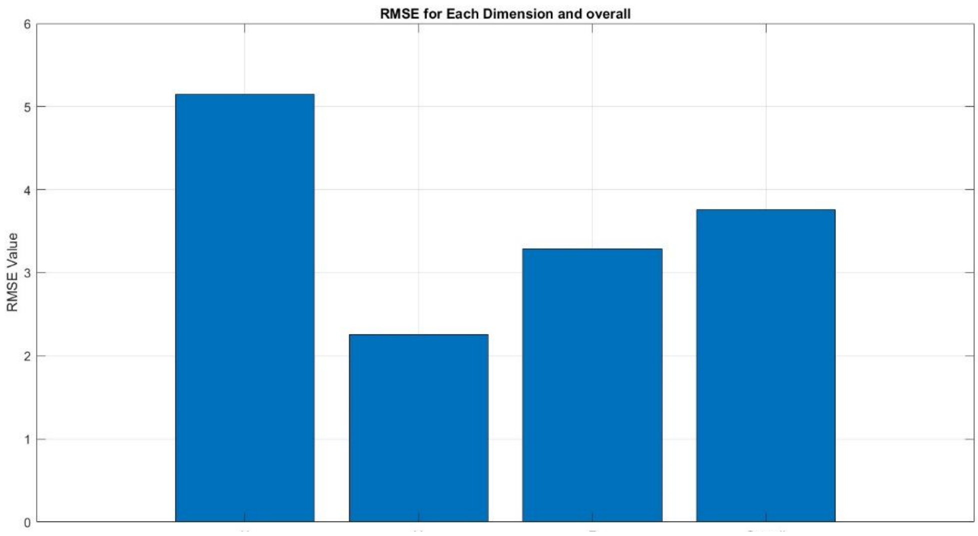


Figure 29: RMSE using two components

4.2.8. Reconstruction using three kinematic synergies

Given the results obtained from the previous step, the analysis was repeated with an incremented number of principal components, which were then three.

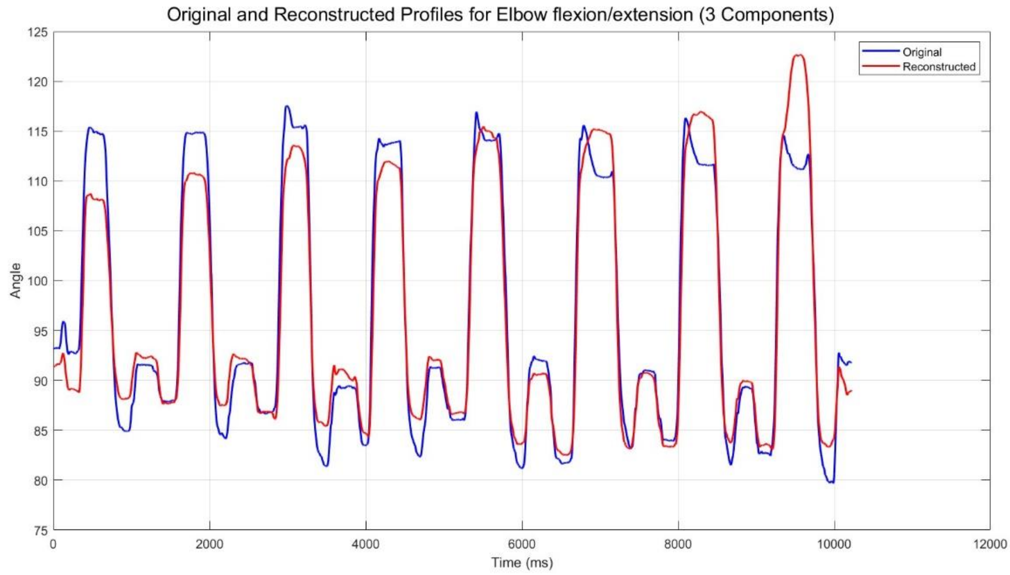


Figure 30: Reconstruction of Elbow flexion/extension using three components

As done beforehand, the investigation was performed previously on a single angle, and then on the whole trajectory.

It can be noticed from Figure 31 that the shape of the angle is smoother than the one using two components even if it is still different from the original one.

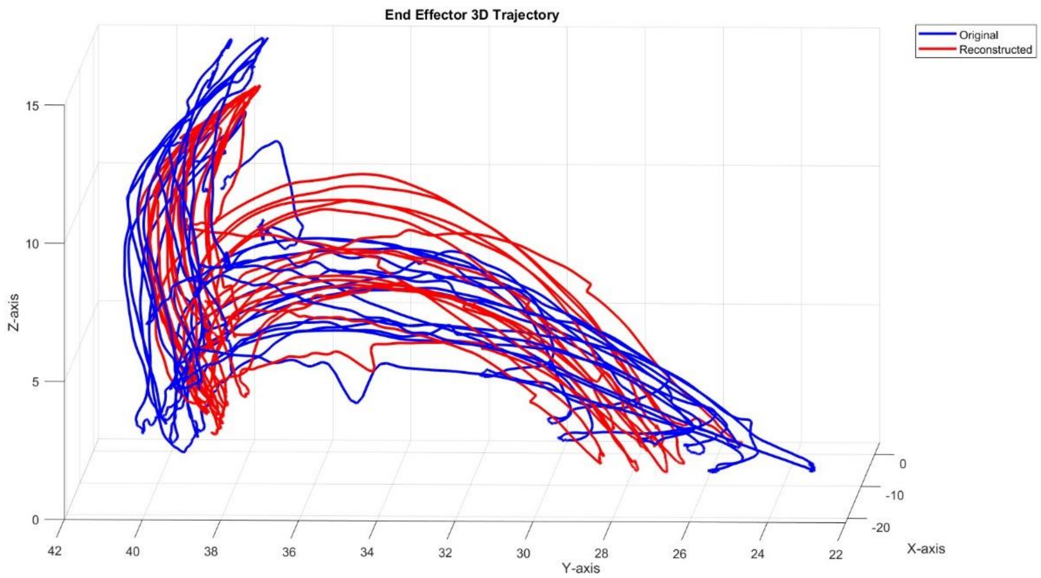


Figure 31: 3D trajectory reconstruction using three components

As expected, it can be observed that in this iteration of the trajectory computation, the results are better than in the previous case, as shown in Figures 32 and 33.

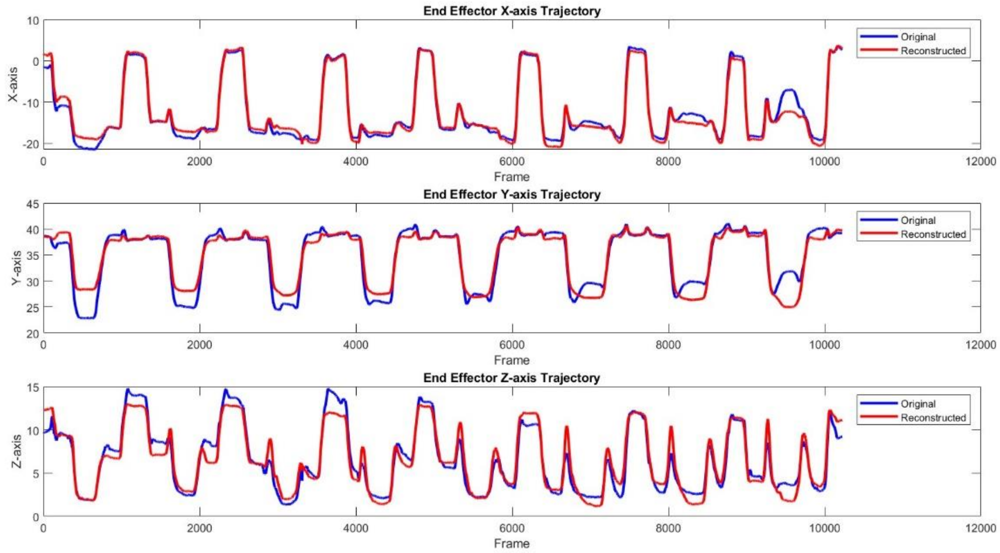


Figure 32: : Dimension per dimension trajectory reconstruction using three components

This improvement can be noticed also terms of RMSE reported in Figure 34.

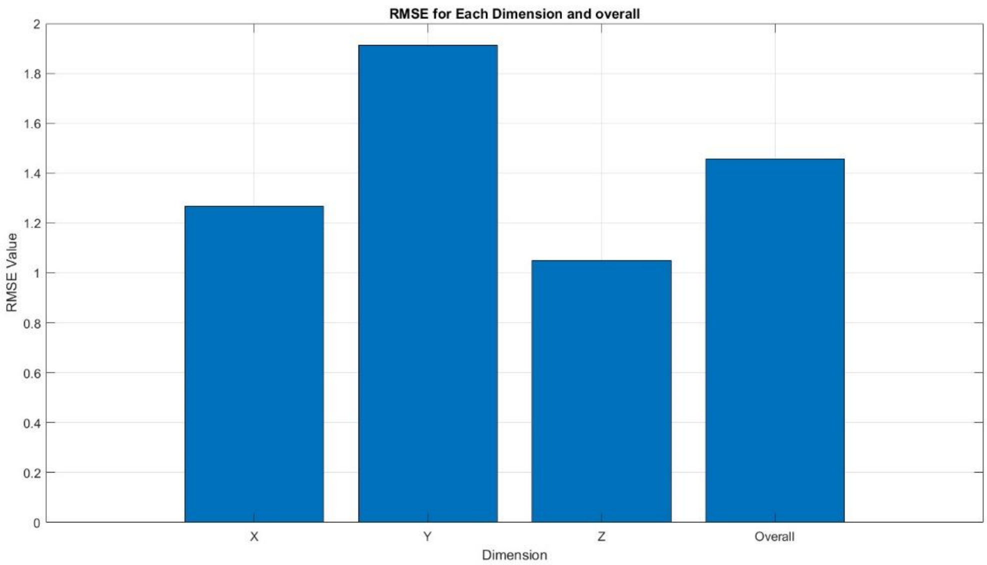


Figure 33: : RMSE using three components

4.2.9. Trajectory reconstruction using four components

As a final computation, the reconstruction step was repeated increasing by one unit the number of principal components used, to evaluate the differences between the other examples.

Once again, the assessment was made on the reconstruction of the 'Elbow flexion/extension' angle profile, and then the EE trajectory shape.

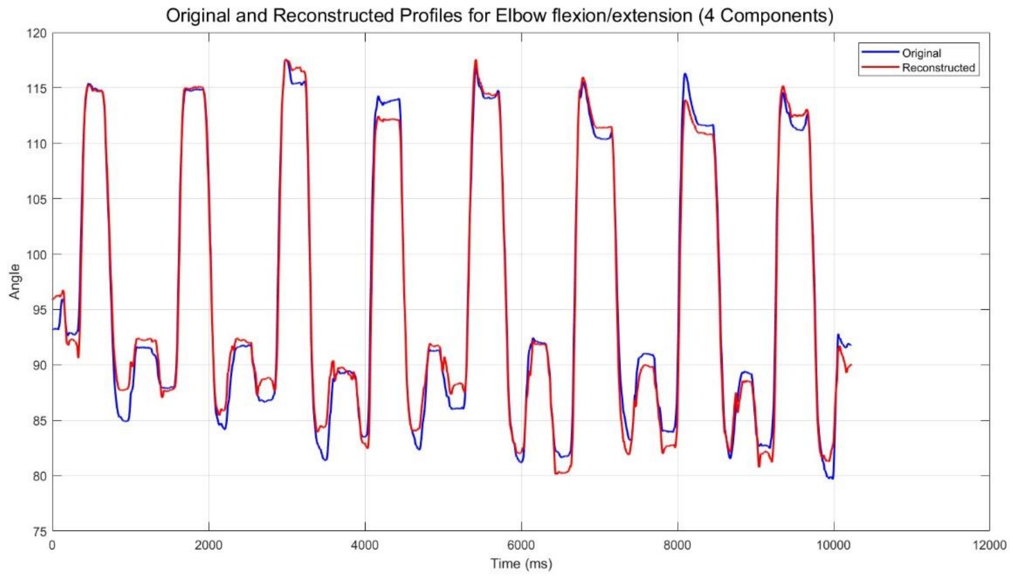


Figure 35: Reconstruction of Elbow flexion/extension using four components

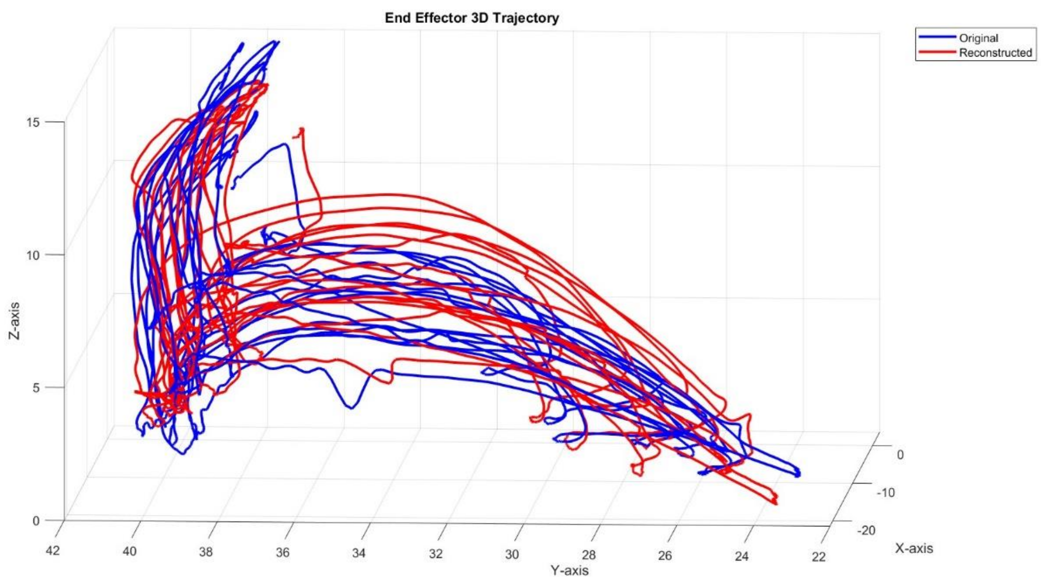


Figure 34: 3D trajectory reconstruction using four principal components

It is possible to observe from Figure 35 that the profile is more comparable to the original one in contrast with the results of the previous iteration.

As for the single angle, it can be noticed that also for the trajectory reconstruction, the results are improved if the number of kinematic synergies used for reconstruction is increased. These results can be observed from Figure 36 and 37.

Additionally, it can also be noted that the RMSE has once again decreased (Figure 38).

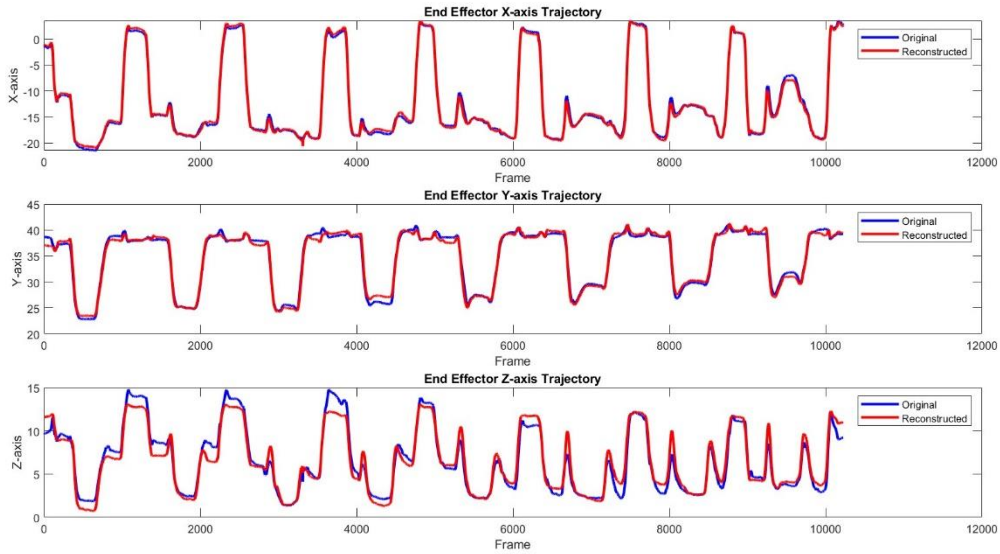


Figure 37: Dimension per dimension trajectory reconstruction using four principal components

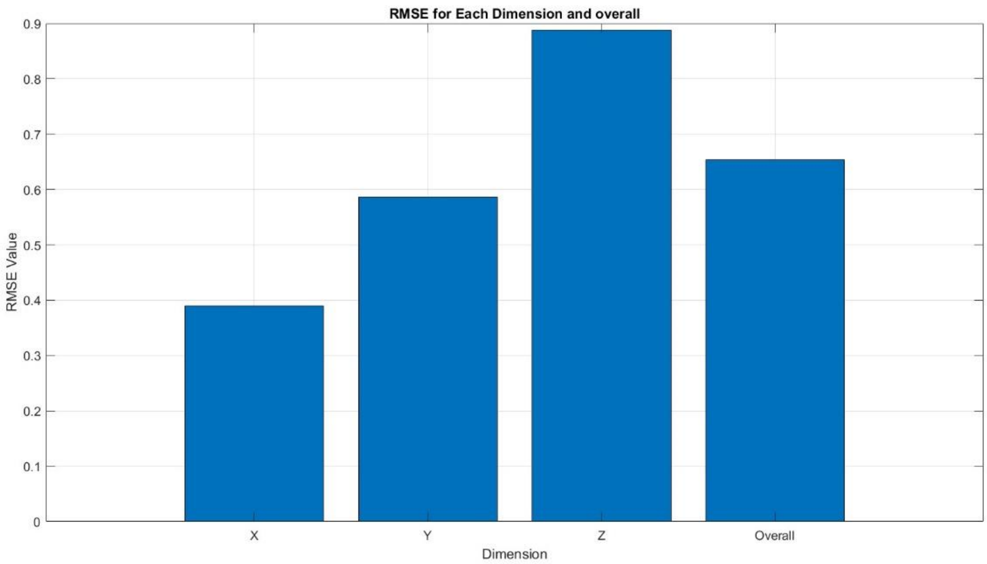


Figure 36: RMSE using four synergies

4.3. Comparison between all individual's motor skills

In this section, the results obtained from the analysis of the properties of the synergies per everyone's motor skills will be outlined, highlighting the possibility of patterns or similarities among the users.

The description is going to be divided per each task, illustrating the results per everyone, giving particular attention to the first principal component of each one of them.

The property displayed in the tables, as it was the most significant, was the influence of the joints in the synergies.

After that are showed the results of the trajectory reconstruction, specifically on the values of RMSE obtained using one, two or three PCs.

The empty grey rows in the tables shows that there was an error in the experiment for that repetition, so no data was obtained. Instead, if the cell is just white and empty, it means that no data is there as the second synergy was unnecessary to reach 90% of the variance.

4.3.1. Anterior reaching at rest height (on the plane) - ARR (motor skill 1)

User	Q0	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1	0,02	0,24	0,28	0,51	0,57	0,52	0,05	0,04
2	0,03	0,08	0,11	0,68	0,58	0,43	0,02	0,07
3	0,03	0,02	0,13	0,59	0,59	0,53	0,07	0,04
4	0,01	0,07	0,03	0,71	0,52	0,45	0,05	0,07
5	0,07	0,04	0,19	0,49	0,61	0,57	0,04	0,10
6	0,00	0,00	0,22	0,66	0,52	0,49	0,06	0,02
7	0,01	0,06	0,25	0,65	0,52	0,49	0,02	0,02
8								
9	0,09	0,05	0,22	0,51	0,60	0,57	0,06	0,02
10	0,02	0,21	0,00	0,61	0,55	0,52	0,08	0,02
11	0,05	0,08	0,09	0,65	0,57	0,49	0,02	0,03
12	0,02	0,12	0,16	0,62	0,58	0,48	0,05	0,03
13	0,03	0,32	0,12	0,42	0,61	0,56	0,13	0,02
14	0,03	0,11	0,12	0,64	0,55	0,51	0,01	0,04
15	0,03	0,76	0,07	0,54	0,32	0,06	0,15	0,09
16	0,01	0,57	0,23	0,34	0,36	0,42	0,45	0,02

Table 6: Motor skill one, Synergy 1 (Joint Influences)

User	Q0	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1	0,05	0,93	0,13	0,10	0,23	0,19	0,06	0,05
2								
3								
4								
5	0,07	0,94	0,13	0,20	0,15	0,12	0,06	0,09
6	0,03	0,16	0,19	0,74	0,45	0,42	0,08	0,03
7								
8								
9								
10	0,01	0,59	0,52	0,16	0,31	0,17	0,48	0,05
11	0,06	0,04	0,14	0,73	0,62	0,19	0,09	0,11
12								
13	0,01	0,20	0,34	0,55	0,02	0,24	0,69	0,01
14	0,01	0,20	0,34	0,55	0,02	0,24	0,69	0,01
15	0,02	0,14	0,05	0,47	0,48	0,70	0,17	0,09
16	0,01	0,12	0,01	0,82	0,22	0,49	0,13	0,03

Table 7: Motor skill one, Synergy 2 (Joint Influence)

User	Using one Synergies	Using two Synergies	Using three Synergies	Using four Synergies
1	14,69	1,75	1,44	0,72
2	4,69	3,40	1,82	0,62
3	6,15	4,85	0,87	0,86
4	5,91	5,30	0,81	0,75
5	8,66	1,75	1,41	0,85
6	8,62	6,05	1,38	1,20
7	4,70	2,33	1,54	0,44
8				
9	5,00	2,48	2,09	0,75
10	10,34	4,89	4,32	2,75
11	6,38	4,63	2,19	1,41
12	6,14	4,26	1,12	0,56
13	6,34	6,18	4,55	2,40
14	4,79	3,30	1,28	0,57
15	13,64	9,45	8,57	4,83
16	19,03	16,31	6,94	2,97

Table 8: 3D RMSE results for motor skill one

As it can be observed from Table 6, while executing motor skill number one, the joints which changes the most are usually number four, five and six (Shoulder axial rotation, Elbow: flexion/extension, Forearm pronation/supination). Angles one and eight (Trunk flexion, Ulnar radial/ deviation) instead, are the one least shifting for all the individuals, on average.

As noted, once the data needs a second principal component to cover the ninety percent of the variance of the dataset, the second synergy has a different order of most influential joints.

4.3.2. Anterior reaching at shoulder height (in the space) -ARS(motor skill 2)

It can be observed from Table 8 that the most relevant joints, for what concerns their movement, are once again number four, five and six.

User	Q0	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1	0,11	0,23	0,38	0,54	0,52	0,45	0,13	0,08
2	0,10	0,07	0,30	0,65	0,51	0,36	0,27	0,07
3	0,05	0,01	0,24	0,65	0,54	0,45	0,12	0,06
4	0,05	0,10	0,14	0,71	0,49	0,43	0,18	0,07
5	0,12	0,02	0,33	0,55	0,53	0,50	0,18	0,09
6	0,05	0,03	0,33	0,67	0,50	0,42	0,09	0,05
7	0,05	0,00	0,28	0,75	0,44	0,35	0,16	0,06
8	0,10	0,06	0,19	0,52	0,66	0,34	0,33	0,13
9	0,17	0,06	0,34	0,53	0,55	0,48	0,17	0,04
10	0,04	0,06	0,26	0,59	0,57	0,49	0,11	0,07
11	0,11	0,08	0,23	0,60	0,57	0,45	0,18	0,10
12	0,07	0,12	0,30	0,68	0,50	0,41	0,08	0,02
13	0,08	0,34	0,36	0,53	0,57	0,38	0,02	0,01
14	0,07	0,09	0,24	0,68	0,48	0,48	0,10	0,05
15	0,08	0,18	0,18	0,58	0,63	0,37	0,23	0,13
16	0,11	0,11	0,24	0,60	0,55	0,49	0,14	0,03

Table 9: Motor skill two, Synergy 1 (Joint Influences)

The least relevant joints instead, are number one, two and eight.

These results demonstrate how are the pseudo-movements characterized and show the fact that they are similar to the ones related to the first motor skill.

This result could have been hypothesized, as task number one and two are both 'Anterior reaching' movements, even though one is on the plane and the other in the space.

User	Q0	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1	0,12	0,90	0,20	0,15	0,22	0,25	0,01	0,04
2	0,06	0,11	0,02	0,66	0,54	0,51	0,09	0,00
3								
4								
5	0,05	0,03	0,27	0,70	0,38	0,54	0,04	0,04
6	0,07	0,07	0,10	0,71	0,47	0,51	0,03	0,04
7								
8	0,03	0,48	0,29	0,56	0,10	0,46	0,37	0,11
9	0,28	0,34	0,19	0,61	0,36	0,52	0,03	0,00
10	0,01	0,39	0,30	0,52	0,25	0,34	0,55	0,09
11	0,05	0,48	0,28	0,51	0,22	0,30	0,50	0,16
12								
13	0,01	0,21	0,29	0,62	0,08	0,65	0,07	0,24
14	0,01	0,21	0,29	0,62	0,08	0,65	0,07	0,24
15	0,10	0,17	0,07	0,66	0,17	0,39	0,58	0,05
16	0,08	0,48	0,55	0,52	0,28	0,21	0,20	0,15

Table 10: Motor skill two, Synergy 2 (Joint Influence)

User	Using one Synergies	Using two Synergies	Using three Synergies	Using four Synergies
1	13,13	1,94	0,94	0,93
2	5,64	4,25	3,88	2,70
3	5,86	5,10	3,01	1,06
4	6,16	4,60	3,17	0,77
5	7,09	6,42	2,23	2,05
6	9,25	7,48	2,91	1,53
7	5,46	4,29	1,43	1,09
8	6,57	6,13	6,04	3,01
9	5,87	5,40	3,96	1,09
10	7,48	6,97	5,78	2,71
11	6,13	5,90	3,79	1,42
12	7,22	4,81	2,62	0,55
13	6,33	5,57	2,01	1,08
14	4,68	3,97	3,02	2,92
15	6,83	6,78	4,80	4,65
16	8,14	5,86	5,50	0,86

Table 11: 3D RMSE results for motor skill two

4.3.3. Hand to mouth with object – HMO (motor skill 3)

User	Q0	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1	0,07	0,34	0,48	0,69	0,22	0,23	0,27	0,07
2	0,00	0,03	0,00	0,03	0,02	1,00	0,02	0,01
3	0,03	0,07	0,08	0,13	0,03	0,98	0,04	0,00
4	0,03	0,09	0,27	0,92	0,00	0,13	0,22	0,01
5	0,20	0,06	0,50	0,68	0,27	0,35	0,23	0,05
6	0,03	0,51	0,39	0,49	0,21	0,30	0,44	0,10
7	0,03	0,12	0,29	0,86	0,17	0,32	0,15	0,02
8	0,00	0,03	0,03	0,02	0,02	1,00	0,05	0,00
9	0,01	0,04	0,01	0,01	0,02	1,00	0,05	0,01
10	0,00	0,02	0,01	0,01	0,05	1,00	0,02	0,01
11	0,04	0,05	0,01	0,32	0,04	0,93	0,18	0,04
12	0,06	0,10	0,44	0,85	0,08	0,25	0,04	0,07
13	0,00	0,57	0,35	0,03	0,31	0,68	0,02	0,03
14	0,01	0,37	0,03	0,15	0,41	0,28	0,77	0,05
15	0,01	0,04	0,04	0,08	0,03	0,99	0,08	0,02
16								

Table 12: Motor skill three, Synergy 1 (Joint Influence)

User	Q0	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1	0,00	0,41	0,07	0,06	0,39	0,56	0,59	0,05
2	0,03	0,14	0,42	0,80	0,41	0,02	0,06	0,01
3	0,10	0,15	0,43	0,76	0,02	0,13	0,40	0,18
4	0,01	0,22	0,01	0,03	0,03	0,84	0,44	0,23
5	0,28	0,55	0,16	0,03	0,19	0,02	0,73	0,10
6	0,06	0,06	0,30	0,26	0,00	0,33	0,84	0,13
7	0,01	0,13	0,05	0,28	0,01	0,94	0,17	0,00
8	0,01	0,57	0,35	0,25	0,37	0,06	0,58	0,03
9	0,36	0,15	0,54	0,69	0,10	0,00	0,26	0,08
10								
11	0,00	0,45	0,15	0,72	0,34	0,30	0,07	0,17
12	0,01	0,41	0,03	0,15	0,13	0,20	0,86	0,07
13	0,02	0,03	0,07	0,55	0,03	0,03	0,82	0,12
14								
15	0,04	0,24	0,11	0,91	0,27	0,06	0,00	0,15
16								

Table 13: Motor skill three, Synergy 2 (Joint Influence)

User	Using one Synergies	Using two Synergies	Using three Synergies	Using four Synergies
1	1,72	0,90	0,52	0,39
2	5,94	3,76	1,46	0,65
3	6,06	3,62	1,49	1,30
4	3,35	3,00	0,93	0,89
5	1,73	1,24	1,20	0,50
6	7,11	6,94	4,15	2,74
7	4,42	1,32	1,10	0,71
8	9,79	7,83	3,53	2,14
9	3,70	2,83	1,05	0,99
10	7,82	2,21	1,49	1,28
11	11,07	2,74	1,51	1,41
12	3,25	1,17	1,08	0,59
13	5,20	4,86	4,13	2,77
14	4,97	3,85	3,18	1,25
15	10,30	9,14	4,88	1,21
16				

Table 14: 3D RMSE for motor skill three

This motor skill was quite different from the previous two, as it was easier to make and needed less time to be fully executed (it was observed from the number of time samples).

It can be observed that this time, all the individuals needed at least two synergies to cover the 90% of the variance. In addition, this time the most influential joints for the most important principal component, are number six, number four and three.

The least relevant ones, still from a movement point of view, are the number one and eight. Finally, the complementarity of the synergies can be observed, as the most important angles are not the same for both.

4.3.4. Hand to mouth without object - HMX (motor skill 4)

Still from the binomial of 'Hand to mouth' tasks, here are the results for the version without the object.

This time, motor skill number four does not always need two synergies to cover the ninety percent of the variance.

User	Q0	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1	0,01	0,05	0,05	0,13	0,11	0,98	0,04	0,01
2	0,00	0,08	0,06	0,26	0,10	0,96	0,00	0,01
3	0,00	0,08	0,08	0,40	0,08	0,90	0,10	0,02
4	0,01	0,05	0,06	0,44	0,10	0,89	0,01	0,03
5	0,01	0,10	0,06	0,22	0,11	0,96	0,05	0,04
6	0,01	0,09	0,06	0,23	0,10	0,96	0,04	0,02
7	0,01	0,04	0,11	0,52	0,12	0,83	0,03	0,00
8	0,00	0,00	0,04	0,25	0,11	0,96	0,01	0,03
9	0,01	0,06	0,13	0,24	0,10	0,96	0,02	0,01
10	0,01	0,09	0,08	0,32	0,09	0,94	0,00	0,02
11	0,01	0,11	0,04	0,33	0,05	0,94	0,01	0,00
12	0,00	0,09	0,08	0,27	0,08	0,95	0,03	0,03
13	0,00	0,04	0,04	0,14	0,06	0,99	0,03	0,01
14	0,01	0,10	0,01	0,39	0,08	0,91	0,02	0,01
15	0,00	0,56	0,17	0,71	0,24	0,10	0,29	0,05
16	0,01	0,09	0,15	0,22	0,13	0,95	0,03	0,02

Table 15: Motor skill three, Synergy 1 (Joint Influence)

However, it is observable that as before, joint number four and six are the most influential ones. Number one and eight (trunk flexion and ulnar/radial deviation) are the least ones.

User	Q0	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1								
2								
3	0,01	0,54	0,27	0,64	0,24	0,25	0,33	0,02
4								
5								
6								
7								
8								
9								
10								
11	0,01	0,63	0,17	0,29	0,27	0,04	0,58	0,28
12								
13	0,00	0,42	0,20	0,78	0,19	0,11	0,34	0,07
14								
15	0,01	0,17	0,13	0,37	0,11	0,66	0,60	0,08
16	0,01	0,58	0,22	0,09	0,26	0,17	0,71	0,11

Table 16: Motor skill three, Synergy 2 (Joint Influence)

User	Using one Synergies	Using two Synergies	Using three Synergies	Using four Synergies
1	2,10	0,75	0,49	0,46
2	4,07	1,80	1,19	0,43
3	4,96	1,86	1,06	0,80
4	1,64	1,08	0,55	0,44
5	2,56	1,89	0,92	0,67
6	4,73	1,92	1,31	0,51
7	1,91	1,50	0,80	0,49
8	3,34	2,26	1,60	1,09
9	1,43	1,12	0,60	0,58
10	2,93	1,28	1,11	0,80
11	4,07	1,93	0,90	0,72
12	2,28	1,04	0,77	0,60
13	7,34	3,04	2,26	1,00
14	1,89	1,36	0,75	0,58
15	6,76	7,05	5,93	3,49
16	6,37	4,67	3,51	1,96

Table 17: 3D RMSE for motor skill four

4.3.5. Move object at rest height (on the plane) – MOR (motor skill 5)

User	Q0	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1	0,04	0,43	0,30	0,57	0,58	0,16	0,19	0,04
2	0,03	0,20	0,11	0,65	0,53	0,48	0,12	0,02
3	0,02	0,10	0,10	0,72	0,51	0,24	0,37	0,09
4	0,01	0,13	0,06	0,79	0,50	0,29	0,10	0,07
5	0,06	0,03	0,21	0,71	0,63	0,18	0,10	0,08
6	0,03	0,05	0,18	0,77	0,58	0,12	0,17	0,05
7	0,01	0,05	0,15	0,74	0,50	0,42	0,05	0,04
8	0,01	0,02	0,07	0,23	0,25	0,92	0,17	0,11
9	0,09	0,04	0,24	0,51	0,50	0,62	0,19	0,05
10	0,02	0,15	0,10	0,70	0,57	0,27	0,28	0,04
11	0,05	0,12	0,12	0,54	0,34	0,63	0,41	0,03
12	0,02	0,29	0,20	0,50	0,42	0,66	0,08	0,00
13	0,05	0,53	0,20	0,37	0,51	0,52	0,07	0,04
14	0,04	0,15	0,09	0,76	0,59	0,14	0,16	0,05
15	0,02	0,27	0,00	0,04	0,07	0,95	0,13	0,04
16	0,03	0,23	0,01	0,87	0,10	0,41	0,11	0,03

Table 18: Motor skill five, Synergy 1 (Joint Influence)

This motor skill is going to be like the first two, for what concerns the movements and the time sampled collected.

The task number five and six are similar, as they both have the goal moving an object, either in the space or on the plane.

As it can be observed from Table 9, the complexity of the motor skill made it necessary to have three synergies in separate occasions.

In similarity to the previous cases, joints number four, five and six happen to be the most important for the first synergy.

Furthermore, joint number one results to be the less important most of the times.

User	Q0	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1	0,03	0,89	0,18	0,20	0,31	0,02	0,18	0,05
2	0,01	0,07	0,03	0,36	0,30	0,85	0,23	0,07
3	0,02	0,96	0,05	0,02	0,24	0,02	0,08	0,07
4	0,01	0,01	0,06	0,55	0,40	0,72	0,13	0,07
5	0,08	0,99	0,06	0,00	0,00	0,12	0,05	0,01
6	0,03	0,92	0,02	0,10	0,13	0,35	0,04	0,00
7	0,02	0,92	0,19	0,02	0,08	0,28	0,16	0,04
8	0,00	0,71	0,25	0,49	0,27	0,13	0,29	0,15
9	0,10	0,92	0,11	0,09	0,16	0,30	0,08	0,02
10	0,01	0,06	0,01	0,17	0,21	0,96	0,04	0,01
11	0,02	0,73	0,17	0,02	0,58	0,02	0,26	0,18
12	0,00	0,68	0,00	0,34	0,39	0,27	0,44	0,11
13	0,00	0,15	0,29	0,31	0,04	0,34	0,82	0,08
14	0,00	0,52	0,30	0,33	0,27	0,49	0,46	0,12
15	0,00	0,61	0,09	0,67	0,30	0,09	0,28	0,05
16	0,01	0,91	0,07	0,23	0,33	0,07	0,09	0,01

Table 19: Motor skill five, Synergy 2 (Joint Influence)

User	Using one Synergies	Using two Synergies	Using three Synergies	Using four Synergies
1	13,87	1,76	1,70	1,66
2	6,49	6,36	1,65	1,20
3	12,30	4,23	3,90	1,01
4	8,37	7,48	5,15	1,02
5	12,56	2,05	1,71	1,70
6	11,89	2,71	1,88	1,38
7	6,95	2,07	1,75	1,33
8	9,88	8,63	5,27	1,55
9	7,53	3,49	1,91	1,74
10	10,22	10,02	3,07	2,05
11	10,38	6,39	5,83	1,83
12	8,43	3,68	1,34	1,10
13	5,69	5,69	3,81	1,88
14	5,24	4,27	4,02	3,55
15	14,87	8,70	5,80	3,26
16	17,35	6,90	6,63	3,07

Table 20: 3D RMSE for motor skill five

4.3.6. Move object at shoulder height (in the space) - MOS (Motor skill 6)

User	Q0	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1	0,11	0,30	0,40	0,62	0,48	0,33	0,06	0,11
2	0,05	0,06	0,21	0,39	0,22	0,87	0,01	0,05
3	0,05	0,01	0,25	0,65	0,38	0,59	0,13	0,06
4	0,05	0,11	0,20	0,80	0,47	0,25	0,04	0,12
5	0,13	0,01	0,35	0,68	0,47	0,41	0,06	0,10
6	0,06	0,05	0,33	0,72	0,42	0,41	0,09	0,06
7	0,04	0,01	0,28	0,78	0,35	0,43	0,01	0,10
8	0,06	0,02	0,15	0,43	0,18	0,86	0,01	0,10
9	0,18	0,06	0,28	0,47	0,39	0,71	0,08	0,09
10	0,03	0,10	0,17	0,51	0,29	0,79	0,02	0,02
11	0,09	0,07	0,18	0,52	0,31	0,75	0,16	0,08
12	0,06	0,10	0,28	0,51	0,33	0,73	0,04	0,04
13	0,07	0,32	0,23	0,34	0,37	0,75	0,10	0,09
14								
15	0,02	0,08	0,13	0,33	0,21	0,90	0,11	0,05
16	0,09	0,35	0,25	0,37	0,62	0,26	0,42	0,20

Table 21: Motor skill six, Synergy 1 (Joint Influence)

The final motor skill analysed is also the one more complicated, as the task to execute concerns moving an object in the space.

As it happened for its alternative in the plane, this motor skill needs three synergies in different instances, due to its complexity. Joint six, four and five are once again the ones doing most of the movement in the first principal component. It can be noted once more that angles eight and one, are the ones least moving inside the most important synergy.

User	Q0	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1	0,02	0,78	0,27	0,18	0,29	0,43	0,08	0,07
2	0,05	0,03	0,31	0,72	0,31	0,49	0,18	0,11
3	0,01	0,45	0,13	0,41	0,23	0,72	0,20	0,06
4	0,02	0,13	0,05	0,11	0,32	0,93	0,03	0,06
5	0,02	0,06	0,13	0,30	0,24	0,91	0,03	0,06
6	0,02	0,73	0,15	0,05	0,48	0,06	0,43	0,15
7	0,00	0,30	0,09	0,41	0,02	0,80	0,29	0,10
8	0,02	0,57	0,11	0,70	0,00	0,40	0,02	0,13
9	0,16	0,91	0,18	0,20	0,03	0,27	0,04	0,04
10	0,02	0,15	0,03	0,71	0,32	0,60	0,04	0,04
11	0,00	0,65	0,23	0,54	0,14	0,38	0,27	0,03
12	0,00	0,91	0,09	0,18	0,11	0,12	0,30	0,14
13	0,08	0,54	0,38	0,32	0,18	0,53	0,38	0,03
14								
15	0,03	0,35	0,08	0,88	0,02	0,31	0,03	0,01
16	0,10	0,16	0,47	0,48	0,17	0,42	0,56	0,03

Table 22: Motor skill six, Synergy 2 (Joint Influence)

User	Using one Synergies	Using two Synergies	Using three Synergies	Using four Synergies
1	14,38	5,13	1,85	1,20
2	7,03	7,04	2,38	1,91
3	11,06	8,72	2,96	1,41
4	7,39	6,82	2,34	1,04
5	9,31	9,16	2,72	1,71
6	11,68	8,40	8,18	3,68
7	6,21	5,92	1,70	1,09
8	8,59	7,72	5,59	2,19
9	9,22	3,42	2,33	1,79
10	11,03	10,92	4,46	3,13
11	8,76	6,04	3,03	2,22
12	8,69	3,23	2,03	1,52
13	10,35	7,30	2,67	1,74
14				
15	12,70	9,54	6,60	2,77
16	8,21	7,41	3,82	2,05

Table 23: 3D RMSE for motor skill six

In summary, from the analysis of the six different motor skills, it was possible to observe similarities between the synergies of the different individuals.

Even though there was variability in the way the tasks were executed, it was possible to recognize patterns and the fact that the joint angles moving the most were common in all the instances.

5 Discussion and Conclusion

Rehabilitation using robotic devices has had a breakthrough in the last few years. These kinds of devices, in the supporting motor relearning of patients with disabilities in the upper region of the body, help the therapist to achieve better outcomes and increase the positive effects on the disabled persons.

The purpose of this project was to investigate the kinematic synergies in daily life activities movements, and to verify if they could be the key for a simplified motion planning of the robotic assistive device.

The analysis was performed on individuals repeating six different motor skills, which summarised ADLs, using PCA. The choice went to that approach after extensive research over the scientific literature for identifying assessed methodologies investigating the kinematic synergies. The PCA outcomes confirmed that it was indeed a proper method, as it returned principal components sufficient to describe the variance of the input data in all the instances.

Between all the different individuals' motor skills, it was discovered that they needed the same number of PCs to cover 90% of changes of the angles, and that value was around two/three units. The kinematic synergies were then thoroughly investigated, to identify their intrinsic aspects and connections with the joints involved in their pseudo movements.

During this step the goal was individuating the angles changing the most in each one of the components, the ones with higher values of correlation, and at last the phase relationships between them.

It was possible to notice that the most important joints and the least ones, were repeating in the individuals and the motor skills, detecting a sort of pattern between all the repetitions.

Afterward, the principal components were analysed to observe how much of the overall movement made by each joint during the motor skill, was covered by them. As before, it was possible to observe that there was a pattern between all the instances, especially for the most important principal component in each case.

Additionally, it was studied that the secondary principal components had a complementary behaviour to the first one. As the most influential one regarded specific angles, the other components were affecting other joints, contributing to the execution of the motor skill in their specific way.

Following those observations regarding how much the synergies covered the overall movements, the focus shifted to the motor planning task. The definition of the path of the end effector based on the principal components, needed to be verified and compared with the original one. The results obtained from the reconstruction of the primary dataset regarding the joint angles and the one of the trajectories, provided a clear answer to that goal. It was possible to observe that even though a couple of principal components covered an amount of variance that was considered enough in the preliminary stages of the project (that value was 90%), that choice was not effective in the rebuilding of the trajectory.

It was noticed that the reconstruction was not very accurate using just two kinematic synergies' synthetic movements.

Once the number of components was increased to three, the precision in the recreation of the path made by the end effector was improved, and the improved value of RMSE.

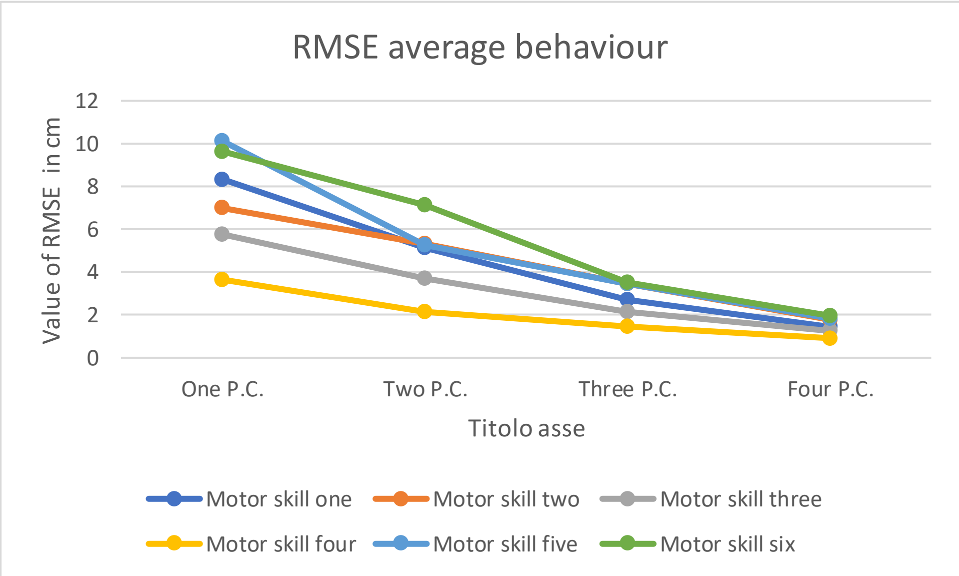


Figure 38: Overall RMSE averages

Reaching four kinematic synergies raised the quality of the outcomes, as each one of them gave their own contribution to covering the total variance of the original dataset.

The fact that each principal component was going to improve the end effector reconstruction was anticipated in the previous analysis step, as it was noted that each one of them focused on describing the variance of difference joints.

If the most important one (for what concerns variance coverage) was going to focus on specific angles and their movements, the next synergies were going to 'fill the gap', and to achieve together the best possible reconstruction of the trajectory.

These outcomes further confirmed the importance of the kinematic synergies in the computation of a trajectory comparable to the one done by individuals in healthy conditions, and its implementation for the motion planning of an upper limb rehabilitation exoskeleton.

As mentioned before, if the focus for the motion planning is on a reduced number of synergies, the control strategy will be simpler than one which focuses on each one of the joints of the upper limb exoskeleton.

The creation of a management approach structured like this, could also improve the way that therapy is performed, managing the exoskeleton more smoothly, as it takes in consideration the joint relationships of the user.

Future developments in this field should subsequently focus on this feature, investigating how that might be implemented in the control algorithms for the robotic device and test their effectiveness.

Observing the way the research was conducted, it is possible to notice that there are limitations to the possible applications of the approach.

As the main focus of the study was just on the path computed in the motor skill, this may be helpful in task like 'reaching' something, but miss some important information on how is adjusted the final part of the exoskeleton.

Therefore, a relevant integration to this study could focus on the orientation of the end effector.

As important is the trajectory to reconstruct the movement, the orientation is decisive to recreate activities in which there is an interaction with the world, for instance grabbing or moving objects.

Provided that, it would be a key development to reproduce an orientation as much as possible similar to the one assumed by the hand in healthy conditions.

Such solution would be essential in the goal of reaching the best possible rehabilitation with an exoskeleton.

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List of Figures

List of Tables