

Louvain School of Management

**End-User Interaction by
Electromyography: the case of the
Thalmic Myo armband**

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Abstract

The past two decades have witnessed a rapid and worldwide rise in power of the smartphones' usage. From this expansion emerged a competition between the visual-based manner of interacting with mobile devices and the visual attention required from the users towards their environment - crucial in multiple mobile contexts (e.g. driving, running, cycling). Given that context, various methods of interaction that utilize senses beyond vision, qualified as *eyes-free* methods, have been developed during the past years. These methods are based on gesture recognition and the first chapter of this work aims at giving the big picture of it by introducing the most predominant techniques and by ending up with the one on which the device of interest in this work, the Myo armband from Thalmic Labs, relies on. More generally, the scope of this work is twofold. The first part consists in a systematic review of the literature in order to draw up an inventory of the various applications based on the Myo armband. While the first part tends to be theoretical, the second one is more practical and is dedicated to an elicitation study where an application, also focused on the Thalmic Myo armband, has been expressly created for this purpose. This study allowed to draw up a catalogue of gestures to be implemented in the Myo armband in case the application was to be developed.

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INTRODUCTION

1.1 Context

In the first half of the 90's, the first commercially available device that could be properly referred to as a smartphone, called *Angler*, emerged from the facilities of the International Business Machines Corporation (IBM) [98]. Then, many manufactures, such as Nokia, Ericsson or Qualcomm began to propose such devices that combine basic mobile phone capabilities with personal digital assistant (PDA) features [135], also known as handheld computers, where only a limited amount of cellular Internet access was at disposal of the user. Some of these features are portable media players, low-end compact digital cameras, pocket video cameras or even GPS navigation units [98]. However, the majority of these devices were bulkier (see Fig. 1.1) and highly more expensive than separate standalone devices either used as mobile phones or PDAs. These drawbacks, combined with others such as low battery life, limited their popularity among the early adopters.

Nevertheless, the mainstream popularity of the smartphones significantly increase when Apple released its first model of the iPhone back in the end of June 2007. An increase which has also been reinforced with the introduction of the Android operating system (Android OS) to the consumer market where the smartphone adoption in the United States bumped by 70 percent in eight years (see Fig. 1.2). By the end of 2022, the number of smartphone unit shipments around the globe reached 1.2 billion and 68 percent of the world's population were smartphone users [78].

This raise in popularity through the whole world can be explained by many technological and ergonomic advances such as :

- sleek and refined smartphones designs;
- large, capacitive and high-resolution touchscreens;
- intuitive and more user-friendly interfaces (e.g. Apple iOS);
- development of various features and applications based on the open-source Android operating system;
- continuous increase in performances, storage capacity and battery life.



Figure 1.1: The Nokia 9110 Communicator, opened for access to keyboard and the Sony Ericsson P900, on the right and the left, respectively. Images taken from <https://urlz.fr/q7U0>.

The keen interest of the public for smartphones impelled new manufacturers to enter the mobile phone market and to differentiate their products from the others through distinctive attributes (e.g. repairable features from Fairphone or stylish products for Apple). However, despite their differences, all smartphones designs intersect in one point : the user interaction with the product relies on vision-based techniques.

As mentioned in [138], this visual-based manner of interacting with the mobile devices may be disadvantageous or even intrusive due to number of factors, such as the need of visual attention - crucial in multiple mobile contexts (e.g. driving, running, cycling) - or the inconvenience of reaching the device from a pocket or a bag to use the display. Hence, various methods of interaction that utilize senses beyond vision have emerged during the past years. Among these, the most prevalent methods involve speech and gestures recognition as the primary modes of communication with

the system, such methods are reviewed in Sec. 1.2. In the scope of this work, gesture recognition based on electromyography is investigated and the corresponding device is presented in Sec. 1.3

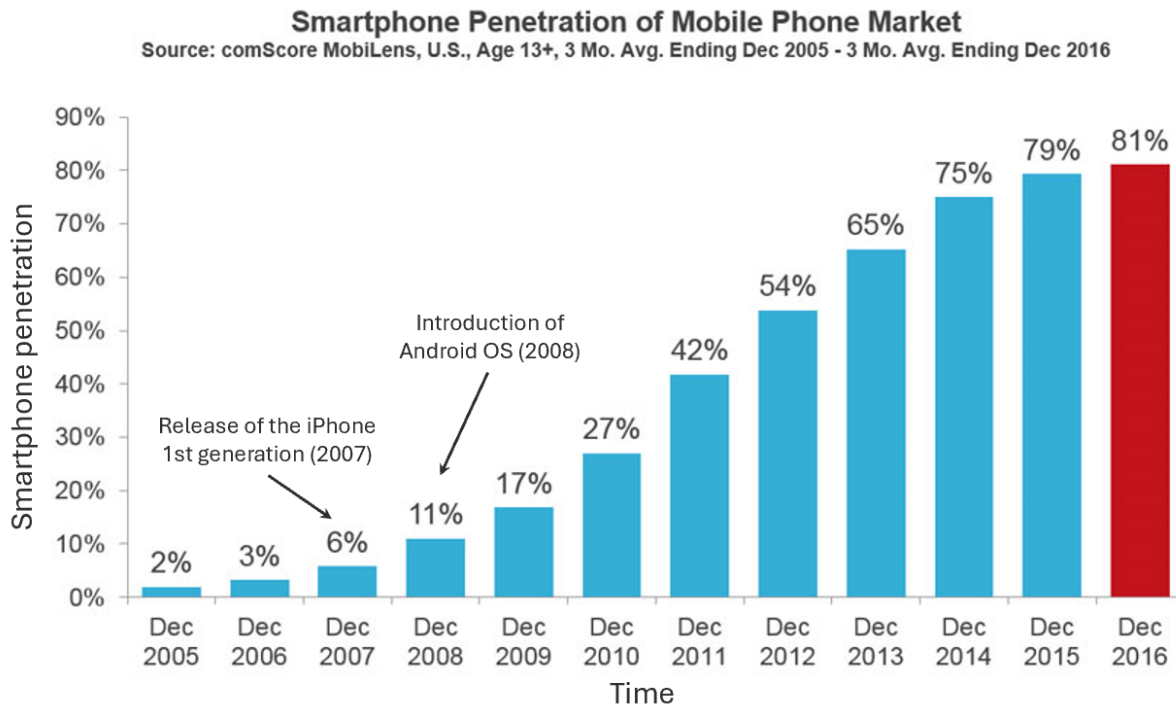


Figure 1.2: Penetration of smartphones on the United States mobile phone market from 2005 to 2016. Image modified from <https://urlz.fr/q800>.

1.2 State-of-the-art

As previously cited, multiple interaction techniques employing senses other than sight have been developed in recent years for operating mobile devices or any electronic unit requiring human inputs. Therefore, this section aims to give the reader some insights on the most popular eyes-free control techniques and is divided into two parts : the speech and the gesture recognition techniques. Note that this work will not cover the technical aspect on which the following recognition techniques rely on in details as it will go beyond the scope of this thesis. Nevertheless, the reader is invited to refer to the papers cited in what follows for more in-depth information.

1.2.1 Speech recognition techniques

Speech recognition, also known as Automated Speech Recognition (ASR) or Speech-to-Text (STT), is a sub-field of computer science and computational linguistics that develops technologies meant to convert acoustic data sequence of speech into a word

sequence that could serve, for example, as an input to a device to perform a given action.

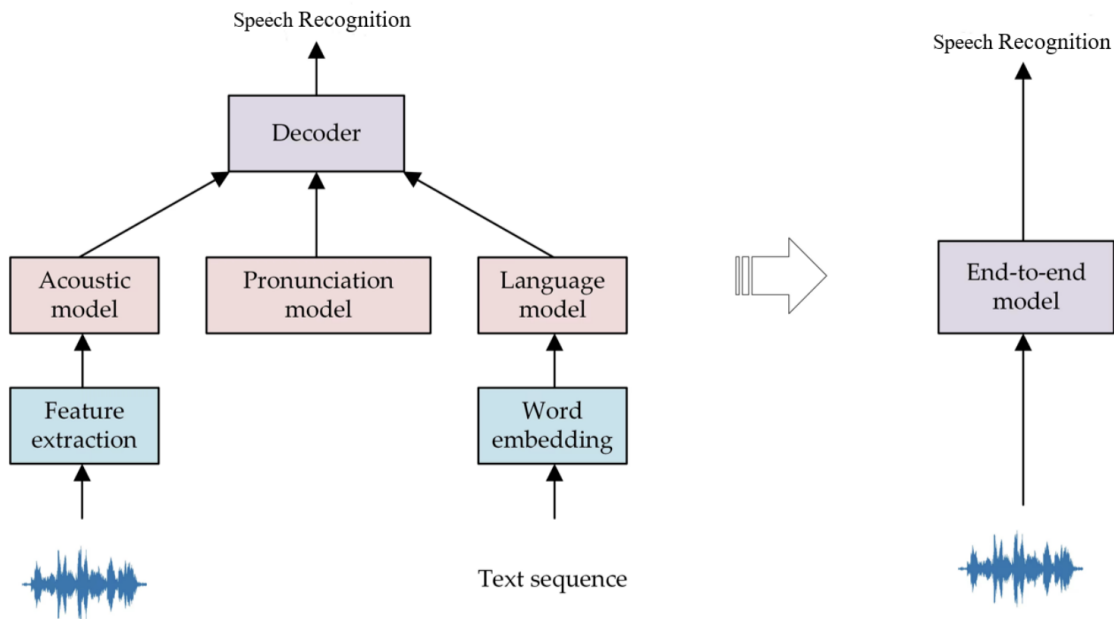


Figure 1.3: Comparison between the classic multi-modules architecture and the end-to-end (E2E) speech recognition. Image taken from [152].

As we can see on Fig. 1.3, classical speech recognition is composed of several modules working in cascade [49]. At first, features are extracted from the input speech where the aim of the acoustical model is to create an output from the incoming speech through pattern matching based on hidden Markov Models (HMM) [63, 97]. In the early stages of the development of speech recognition techniques, Gaussian Mixture Model (GMM) was the most advanced one but has been replaced by Deep Neural Networks (DNN) when advances in hardware and software capabilities allowed the use of deep learning [152]. In other words, the acoustic model takes audio as input and converts it to a probability over characters in the alphabet. Finally, the language model is used to turn these probabilities into coherent and grammatically correct sentences thanks to a training data set.

In recent years, speech recognition has shifted from the structure of multi-modules to an End-to-End (E2E) model, as shown on Fig. 1.3, with the objective to obtain a joint neural network model structure instead of separate modules working in cascade. This change can be explained by the will of simplicity, efficiency and a reduced error propagation compared to multi-modules architectures like the classical ones commonly used in ASR. For more insights, [105] covered most of the aspects of E2E models in their work.

The applications of speech recognition are numerous with fields varying from voice dialing and call routing (e.g. *Siri* from Apple) to home automation solutions (e.g. *Alexa* and *Google Assistant* from Amazon and Google, respectively) and key words search, even with sub-field in the air traffic control. Nevertheless, speech recognition is not always an ideal option. In fact, situations can occur where private matters can enter in conflict with the public - if someone wants to send a sensitive message while surrounded by other people which are not involved in the communication [31]. More generally, speech recognition can be a problem in noisy environment where a lot of parasite noise could interfere with the user's vocal command, even if noise cancellation methods are continuously improved [24]. To alleviate those issues, another type of eyes-free technique has been developed : the gesture recognition technique. Such a method with its related devices is presented in the next section.

1.2.2 Gesture recognition techniques

As mentioned in [67], gestures can be either dynamic or static, where in the gesture becomes a posture. Moreover, gestures can be classified according to the body parts involved in the gesture. To keep it straight, in this section about gestures recognition, the emphasis will be placed on gestures related to the hands/fingers and the body and not on facial recognition, for example. Generally, when it comes to gesture recognition, two approaches are generally prominent and can be resumed in vision-based and contact-based technologies. Before going any further, the authors would like to point out that the following is greatly inspired from the work of [113] in summarizing the ins and outs of vision-based gesture recognition (VGR).

1.2.2.1 Visual-based approach

Vision-based gesture recognition systems do not depend on human-worn equipment unlike the contact-based technologies, as it will be discussed later. Rather, cameras from various types (infrared, stereo-vision or more traditional monocular cameras) are disposed around the user in order to determine and analyze the motions [113].

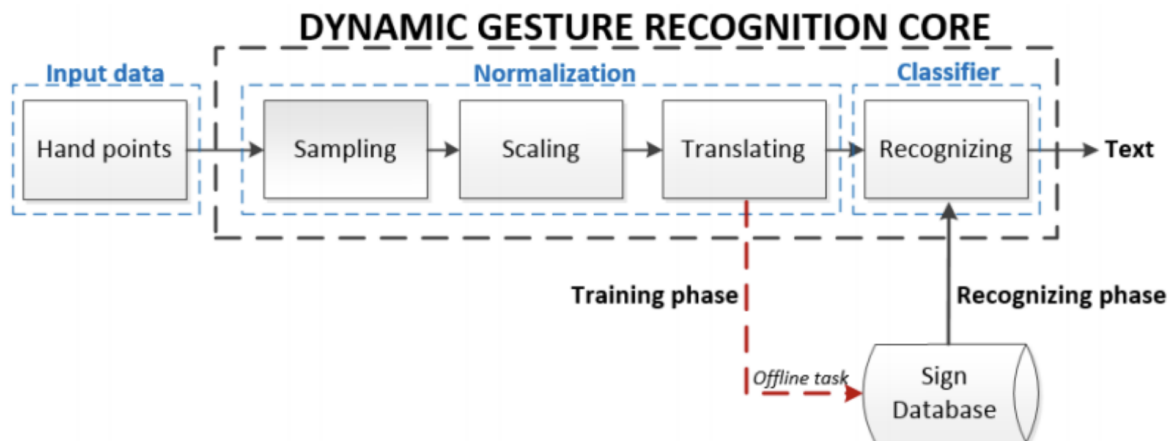


Figure 1.4: Dynamic hand gesture recognition flow utilized in sign language. Image taken from [95].

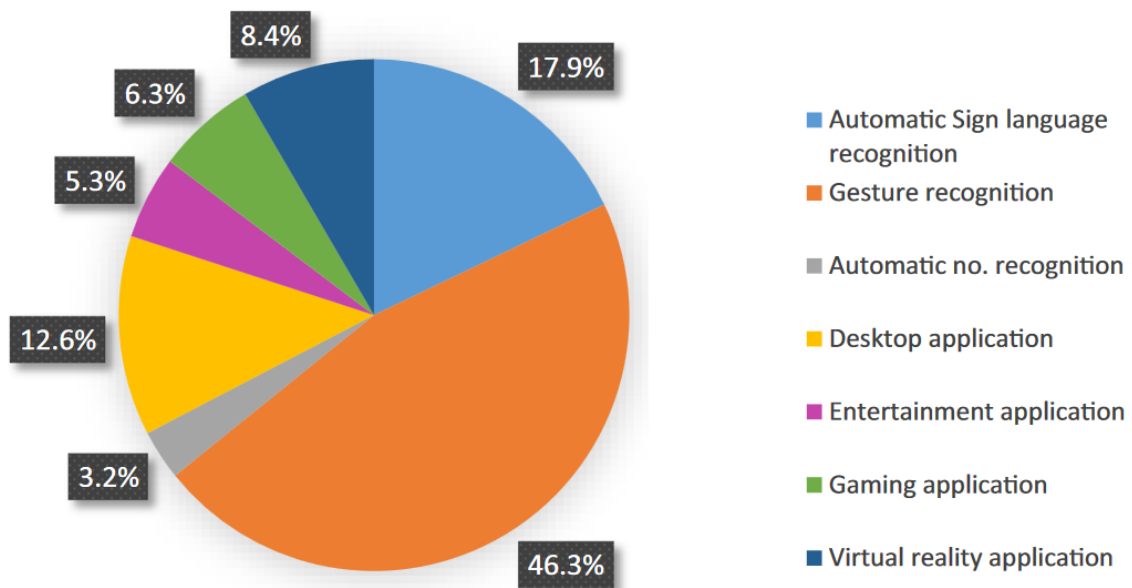


Figure 1.5: Main scopes and applications using vision-based gesture recognition. Image taken from [113].

As previously said, VGR techniques can be classified into dynamic and static gesture recognition. While a template matcher or general classifier can be used for static recognition, detecting dynamic gestures requires the integration of techniques similar to ones seen in the previous section about speech recognition (e.g. Hidden Markov Models or Deep Neural Networks) [95, 144]. The use of such techniques take place in the *Classifier* block as shown on Fig. 1.4.

Based on Fig. 1.5, one can see that many fields of application exist for the vision-based techniques, such as:

- **Industrial applications** where gestures can be used to control robot hand and arm movements, reducing then the need for physical contact and minimizing the risk of accidents.
- **Virtual or augmented reality (V/AR)** where gesture recognition enhances user immersion and interaction in virtual and augmented environments, as the headset Vision Pro from Apple for example.
- **Desktop applications** with the stereo-vision camera-based device from Leap Motion for example, allowing gesture and position tracking with sub-millimeter accuracy [134] and which could be use as a mouse or be placed on a VR headset.
- **Sign language** where devices can be used to translate sign language gestures into spoken or written language, and vice versa in sight of facilitating interactions between people who are fluent in sign language and those who are not. For example, Nguyen et al. [95] proposed in their work a Vietnamese sign language reader that can successfully recognize 28 static and 7 dynamic gestures taken from the Vietnam sign language dictionary.

1.2.2.2 Contact-based approach

Despite their advantages, vision-based recognition techniques present some inconveniences like the constant camera–human spatial relationships, clear line of sight, and consistent lighting required to properly capture and translate the gestures [137]. Therefore, less invasive sensing methods have been developed based on wearable sensors and detectors. Usually, a 3-axis accelerometer is coupled to other sensing devices to increase the translation’s precision of the gesture that must be recognized by the device [10]. Concerning hand gesture recognition for example, several sensing methods can be found in the literature, such as :

- **Mechanical sensing** which relies on the mechanical properties of a material ¹ to measure the force variation from the volumetric and stiffness changes of the muscle movements to obtain information about the gesture [120]. Combined with the accelerometer, also called as inertial measurement unit (IMU), these mechanical sensing methods can be differentiate into : forcemyography, strain, and flex sensors.

¹Thin and stretchable electrodes mounted closely to the skin or on gloves

- **Acoustical and vibratory sensing** where acoustic waves are generated from an emitter at low (mechanomyography) or high (sonomyography) frequencies and then captured by a receiver in sight of measuring changes in the physical structure of the wrist and forearm, the muscles and the tendons [120].
- **Optical sensing** where a light source is projected on a photodetector at the surface of skin to detect the volumetric changes of blood circulation. The working principle relies on the blood volume changes in the microvascular of skin tissues due to muscle and tendon movements which change the reflected light intensity [120].

In this work, the device in use for gesture recognition, which is introduced in Sec. 1.3, relies on another type of sensing method based on muscle contractions. In fact, these contractions can be captured by electrodes placed on the skin of the user resulting in electric signals as output which are amplified and then translated into a given gesture. This electrical sensing technique is called electromyography (EMG) and its working principle is explained in more details in Sec. 1.4.

1.3 The Thalmic Myo Armband

The objective of this thesis is to investigate the Thalmic Myoarmband, an electromyographic device developed by Thalmic Labs. This device facilitates interaction with various devices and applications through natural hand and forearm movements, recognizing and executing specific commands based on gestures.



Figure 1.6: Myo armband from Thalmic Labs.

Following several rounds of prototyping, the final version of the Myoarmband was released in 2014. Its design allows for comfortable all-day wear, resembling a discreet forearm bracelet [77] (see Fig. 1.6).

The Myoarmband recognizes muscle activity in the hand and forearm through the use of its eight electrodes strategically positioned around the forearm. Additionally, the Myoarmband is equipped with a 3D compass, accelerometer, and gyroscope, enabling it to detect forearm motion and rotation in three-dimensional space [130]. This data is then transmitted to an external device using Bluetooth Low Energy (BLE) technology. Over the years, the Myoarmband has been utilized in various fields, such as prosthetic control, robotics, and virtual reality [33, 48, 110]. In the next section, we will present the various steps that enable a designated gesture made with the Myo armband to be translated into the corresponding command within a specific application. This understanding begins with a detailed examination of the device's components and functionalities. The Myo armband is composed of :

- 8 surface electrodes and 8 x ST 78589 operational amplifier sensors (one for each electrode), which serve as sensors for muscle myoelectric signals.
- 1 x InvenSense MPU-9150, a 9-axis IMU enabling detection of arm movements, comprising a 3-axis accelerometer, a 3-axis gyroscope, and a 3-axis magnetometer.
- A vibration motor for user communication.
- A Freescale Kinetis ARM Cortex M4 120Mhz MK22FN1M MCU processor to manage armband operations.
- A BLE (Bluetooth Low Energy) NRF51822 chip for transmitting data from the device to other devices.
- 2 x 3.7 V - 260mAh lithium batteries.
- Micro-USB connector for recharging the lithium batteries.

Fig. 1.7 displays an illustration of the disassembled Myoarmband.

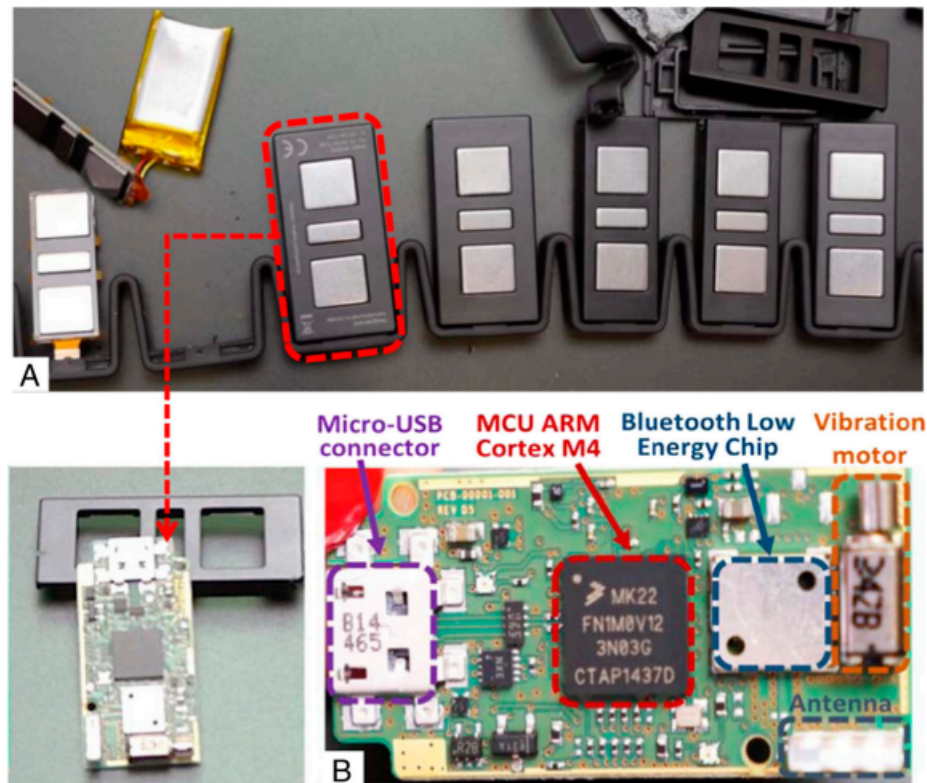


Figure 1.7: View of Myo armband elements (A) and of the electronic control board embedded into the main element (B); the micro-USB connector is highlighted in purple color, MCU ARM Cortex M4 in red, BLE chip in blue, the vibration motor in brown and the antenna in grey. Figure taken from [130].

1.4 Background of electromyographic-based devices

1.4.1 The myoelectric sensors

To understand how myoelectric sensors work, let's first delve into the physical and biological processes involved. When one initiates movement in his arm muscle, an electrical signal known as an action potential travels from a motor neuron in the spinal cord through a nerve fiber to the surface of muscle fibers, as depicted in Fig. 1.8. At this juncture, a neurotransmitter is released and binds to receptors on the muscle fiber surface, initiating an electric impulse that propagates along and within the muscle fiber. Our electrodes detect this signal as it travels through the muscle. Subsequently, the signal triggers the release of calcium ions from the sarcoplasmic reticulum, ultimately leading to muscle contraction [60].

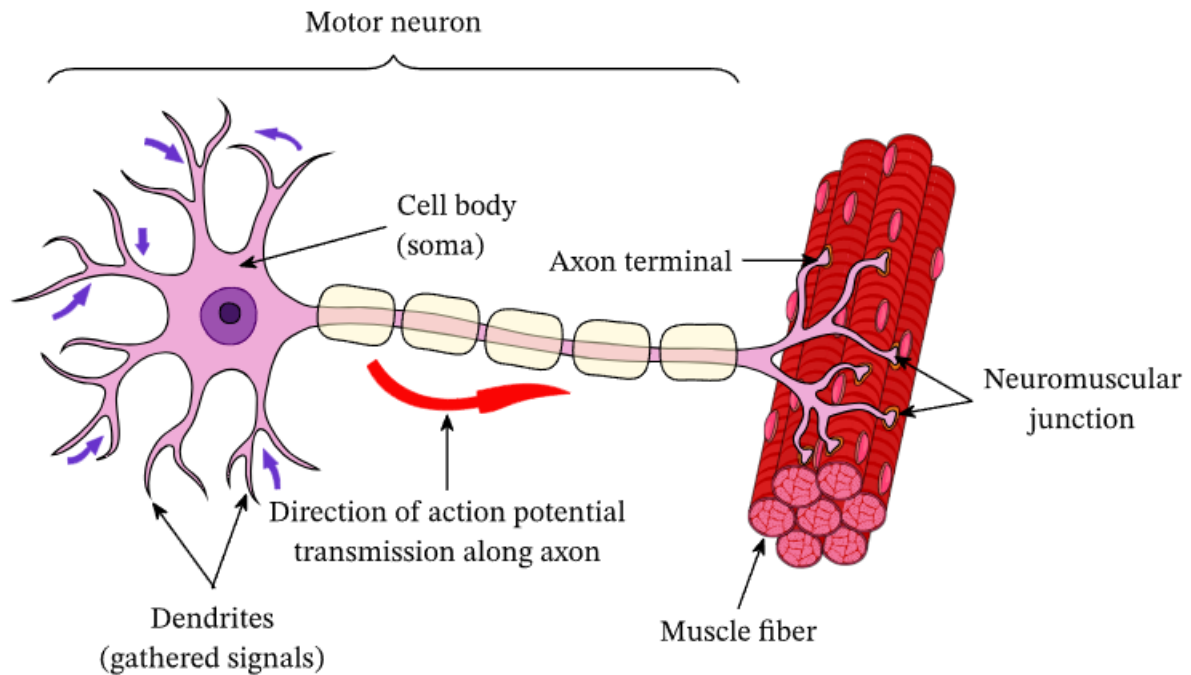


Figure 1.8: A motor unit, several neuromuscular junctions connect the axon terminals of a motor neuron and the muscle fibers. *Credits : Nagwa.com*

The 8 surface electrodes of the myoarmband, positioned around the arm, detect the electric impulses of different muscles. These electrodes are non-invasive, meaning they do not require insertion into the user's muscle with a needle. While non-invasive electrodes are less precise, the information obtained is sufficient for its applications. However, it's important to note that the action potential of a muscle varies depending on the user's physiology and anatomy [53, 60, 112]. Therefore, the accuracy and measurement error also vary and it's imperative for every user to undergo a calibration step before using the device. The electrodes are termed 'active' because they are composed of three conductive materials: one central material that analyzes muscle activity, and two others placed around it that act as a filter, providing immunity to noise.

1.4.2 The InvenSense MPU 91250

This component of the Myo armband serves to detect forearm movement in three-dimensional space. The InvenSense MPU 91250 comprises three primary elements. Firstly, a 3-axis gyroscope detects rotational movements and changes in orientation. Secondly, an accelerometer tracks acceleration and deceleration. Lastly, a 3-axis compass determines the device's position in the 3D space. These sensors utilize microscopic vibrating transducers sensitive to motion. Disturbance of the transducer's

structure alters the electrical potential of the component, enabling the calculation of angular velocity, acceleration, or position [102].

1.4.3 Processing stage

After gathering data on both forearm motion and myoelectric activity, the device proceeds to transmit this information via Bluetooth Low Energy (BLE) to the connected device or application. In Fig. 1.9, we observe an example of the raw signals gathered by the 8 electrodes over a duration of 10 seconds.

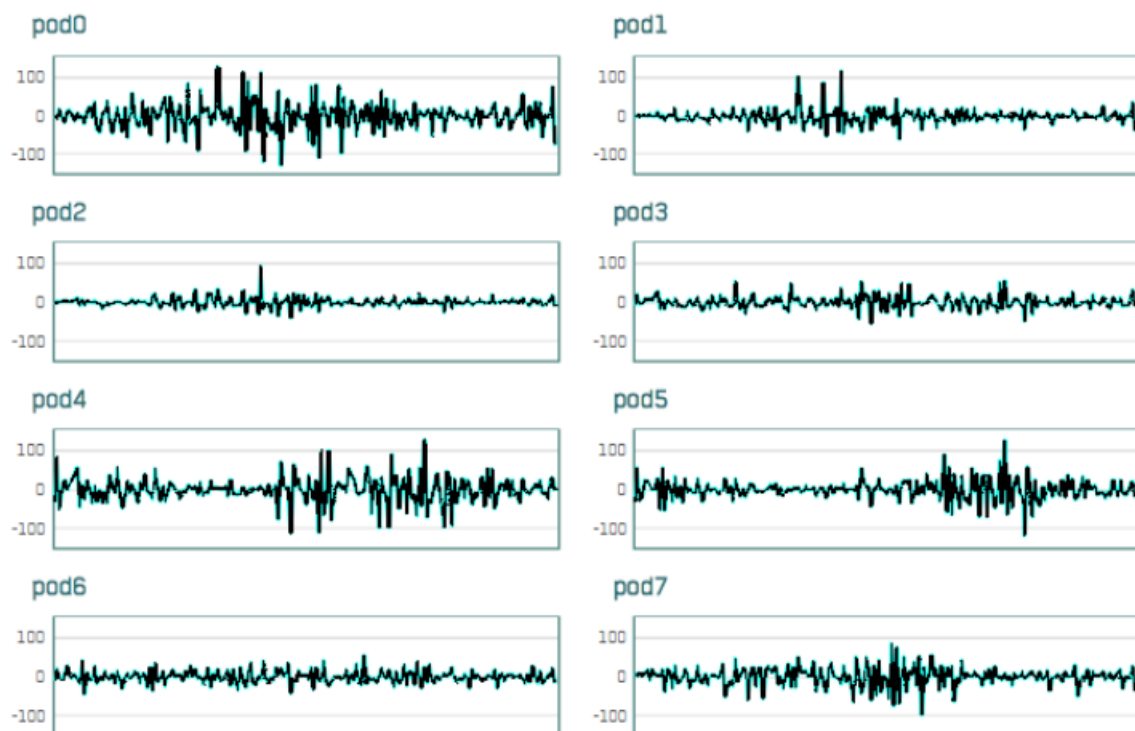


Figure 1.9: Raw signals captured by the electrodes of the Myoarmband in μV [93].

Multiple steps are required to identify the gestures made from the 8 raw signals of the electrodes. These steps constitute the pattern recognition system and consist of three main stages: segmentation, feature extraction, and classification [53]. Once the gestures have been identified using this pattern, the associated commands in the application can be relayed to the user.

1. During the segmentation phase, the raw signals undergo segmentation, separating them into periods corresponding to distinct muscle activity. A segmented signal is termed a "window," with a critical parameter being the window length. It's imperative for the window length to strike a balance—sufficiently long to avoid sacrificing precision yet not excessively long to minimize response delay.

This variable may vary depending on the context, typically ranging around 200 ms [53, 89]. A common approach involves employing overlapping windows, where a fixed window length is used alongside a smaller increment. This ensures that no information is lost during segmentation. In other words, each window partially overlaps with the previous one, ensuring continuity in data capture.

2. Once the windows are separated, the next step is feature extraction. Before being able to classify the windows as particular gestures, it's essential to identify common characteristics linking a gesture to an electrical signal window. To achieve this, we utilize mathematical tools that generate variables dependent on the shape, amplitude, and frequency of the signal, across all eight channels of each created window. This ensures that similar signals produce similar variables, facilitating their classification. Additionally, it's worth mentioning: The more relevant features we include, the more accurately we can identify the signal. However, this comes at the expense of increased computational cost. These features can be computed in the time domain of the signal, but they can also be derived by transforming the signal into the frequency domain using mathematical tools, albeit at a higher computational cost. In what follows, f_k is a discrete electrical signal composed of N samples. It represents the electrical signal from a single window and thus from a single electrode. Therefore, if a 1-second recording is divided into 20 windows, and there are 8 electrodes, there will be 20×8 functions f_k . Here are some commonly used time domain features:

- Root mean square (frequency related features):

$$\text{RMS} = \sqrt{\sum_{k=1}^N f_k^2}$$

- Slope Sign Change (frequency related features) which detect changes in the slope sign of the sEMG signal and count them :

$$\text{SSC} = \sum_{k=2}^{N-1} |(f_k - f_{k-1}) \cdot (f_{k-1} - f_{k-2})|$$

- Mean Absolute value (amplitude related feature) :

$$\text{MAV} = \frac{1}{N} \sum_{k=1}^N |f_k|$$

- Waveform Length (amplitude related features):

$$WL = \sum_{k=2}^N |f_k - f_{k-1}|$$

3. The final stage is the classification step. The classifier will identify the intended movement based on the feature-class sets previously defined. Various algorithms are available for classifying the features of a window into specific commands. For example, Support Vector Machine aims to find the hyperplane that best separates data points into different classes while maximizing the margin between classes. On the other hand, k-Nearest Neighbors determines the class of a data point based on the majority class among its nearest neighbors in the feature space.

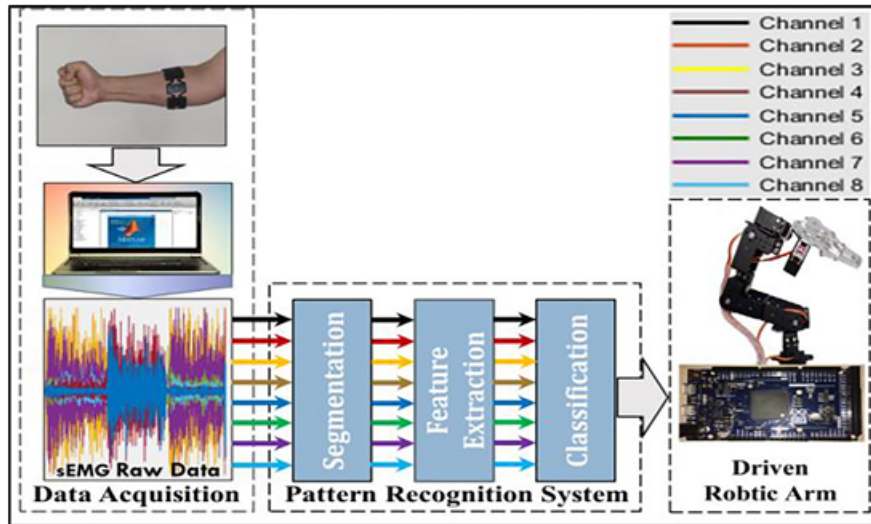


Figure 1.10: Block diagram of the pattern recognition system for a driven robotic arm. Figure taken from [53].

Once the windows have been classified, the commands linked to the recognized gestures can be activated on the external device. A block diagram of the entire process is depicted in Fig. 1.10.

1.5 Objectives and outlines of the thesis

As mentioned in Sec. 1.1, the visual-based manner of interacting with the mobile devices may enter in competition with the visual attention required from the user towards its environment - crucial in multiple mobile contexts (e.g. driving, running, cycling). Given that context, various methods of interaction that utilize senses beyond vision, qualified as *eyes-free* methods and presented in Sec. 1.2, have emerged during the past years. More specifically, this chapter aimed at introducing gesture recognition techniques by ending up with the device of interest in this work : the Myo armband from Thalmic Labs. The scope of this work is twofold.

At first, and following the introduction of Thalmic Myo armband and the description of its working principle, the Chapter 2 will provide a systematic review of the literature in order to identify and analyze the diverse applications based on the Thalmic Myo armband.

Then, the Chapter 3 will propose an elicitation study where the practical situation is about handling phone's functionalities while biking without directly interacting with the phone itself. The main motivation being to allow the user to control its phone and to be constantly aware of its environment at the same time.

Finally, the Chapter 4 will summarize the main achievements of this thesis and will finally provide some perspectives for possible future work.

SYSTEMATIC REVIEW

2.1 Introduction

The systematic review of the literature (SRL) aims at identifying and analyzing scientific articles on a specific topic at a given time to draw conclusions on the matter. It follows a rigorous and well-defined procedure, which must be reproducible. In this work, the subject of the SRL is *"What are the diverse applications of the Myo armband device ?"* and the objectives are multiple :

1. Identify similarities and draw connections between the different applications of the armband.
2. Map the main fields of application of the device.
3. For each field, identify similarities in the gestures used and other relevant aspects.

This study will be presented in three sections. We will start by explaining the methodology used, followed by presenting overall data on the identified literature, and finally, we will discuss more in detail the comparison between the articles from the same application domains of the Myo armband.

2.2 Methods and procedures

The study is conducted in four phases: identification, screening, eligibility, and inclusion, which will be detailed to demonstrate the reproducibility of the method. A diagram illustrates these phases in the form of a PRISMA flowchart (see Fig. 2.1),

standing for Preferred Reporting Items for Systematic Reviews and Meta-Analyses. Our procedure follows the methods used in [129] and [113].

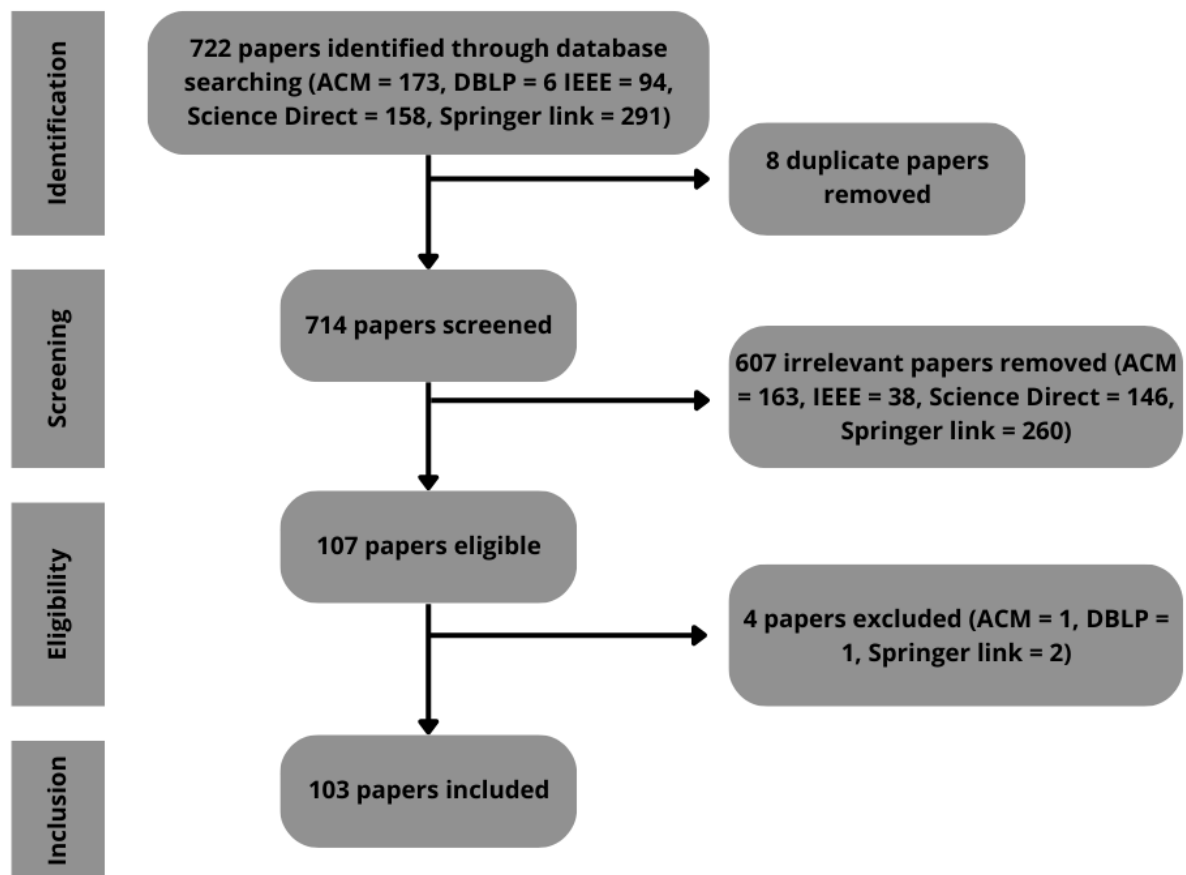


Figure 2.1: PRISMA diagram for the SLR procedure.

Before starting the procedure, it is essential to establish the research question that will guide the entire study. Initially, we considered "What are the Diverse Applications of Electromyographic Armband Devices?". However, since the Myo armband also includes an inertial measurement unit (IMU), we decided to refine our question. This unit, equipped with an accelerometer, gyroscope, and magnetometer, significantly enhances the device's functionality by allowing a broader range of applications. Therefore, the question evolved into "What are the Diverse Applications of the Myo Armband?" to better capture the full potential of the device.

2.2.1 Identification

Based on this research question, we will identify two keywords that will be consistent across all database searches: "myo armband" and either "application" or "using." To ensure the method is reproducible and systematic, we will create a query that remains the same for each database search, using these two keywords. The query is as follows:

Q = ("myo armband" AND ("appli*" OR "using" OR "use*"))

The asterisks (*) indicate that the word can have various endings, allowing for terms like "application" or "applied" with "appli*". Since the Myo armband was developed and commercialized in 2014, we also applied a filter to include only papers published from 2014 onwards. Using this query across five different databases (IEEE Xplore, ACM, DBLP, Science Direct, and Springer Link) and deleting the duplicates, we identified 714 papers. The papers were identified on the 25 of april 2024.

2.2.2 Screening

To assess the relevance of each article, we applied specific criteria. Regarding content, we retained only papers that explicitly mentioned an application of the Myo armband in the title or abstract, as this is the focus of our study. Papers that merely referenced the device as an example of an EMG device were excluded. Additionally, we included only papers written in English, but we did not impose any criteria on the format; for instance, we included master's theses. Papers that did not mention a practical application but used the Myo armband as a tool to evaluate a mathematical classifier were also retained. These will be analyzed further in the thesis. Through this process, 607 papers were removed from the study, mostly because they did not mentionned an application of the Myo armband in the title or the abstract.

2.2.3 Eligibility

In this third step, we examined the content of each paper more closely and excluded those where the objective was not an application of the Myo armband, even if the device was mentioned in the abstract. For example, M. Sathiyararayanan et al. [87] states in its abstract: "a wearable device called MYO Armband is being adopted in physiotherapy treatment," but the actual purpose of the study is to use another connected device, the Leap Motion, to achieve similar outcomes. Consequently, this paper was excluded because its focus was not on demonstrating an application of the Myo armband, despite mentioning it in the abstract. Four papers were removed, leaving a total of 103 papers that aim to explore an application of the Myo armband.

2.2.4 Inclusion

The papers were compiled into a spreadsheet and manually reviewed to highlight specific features. Initially, after reviewing all the papers, we identified four main domains of application:

- **Health Sciences:** including papers that utilized the Myo armband as a rehabilitation prosthesis, biomedical tool, or support for medical studies.
- **Robotics:** where the Myo armband was used to control, operate and interact with an external robot or drone.
- **Computational Studies:** the device was employed to assess the validity of neural networks or machine learning algorithms, or to evaluate the precision of the device by comparing it with other similar devices.
- **Lifestyle and Recreation:** involving everyday applications such as recognizing smoking behavior or analyzing leisure activities like sports or music.

Each paper was associated with one of these domains. Additionally, we categorized study contexts into three categories: participants, environment, and device where multiple data were recorded. The latter are regrouped with their corresponding category in Tab. 2.1.

Table 2.1: Categories used for the papers' classification with the their relative data that have been recorded.

Category	Data recorded
Participants	1. Number of participants 2. Health conditions 3. Gender and age
Device	1. Number of devices used 2. Algorithms and software utilized 3. Other devices used in the study
Environment	1. Location of the study 2. Number and placement of the Myo armband on the participant's body
Device's related features	1. Gestures programmed for the specific commands in the application 2. Algorithm of classification used 3. Date of publication

Not all papers provided all the sought-after features, and almost none addressed criteria related to the location of the study environment. Furthermore, a copy of this spreadsheet is provided in the appendix via a link. By using Excel functions such as "COUNTIF()", COUNTIFS(), and AVERAGEIF()" to count occurrences of certain

parameters based on one or more conditions, we conducted meaningful analyses, presented in the following section.

2.3 Results : an overall descriptive analysis

In this section, we will present overall results from all the papers without considering their specific application domains.

2.3.1 Yearly publications trend

In Fig. 2.2, we can observe the distribution of the 103 papers by their year of publication along with its trend (red curve) which is given by third-order polynomial interpolation. No papers were published in 2014, the year the device was released. A strong upward trend is observed until 2018, when the number of papers decreased significantly. This decrease coincides with the year the Myo armband was no longer commercialized.

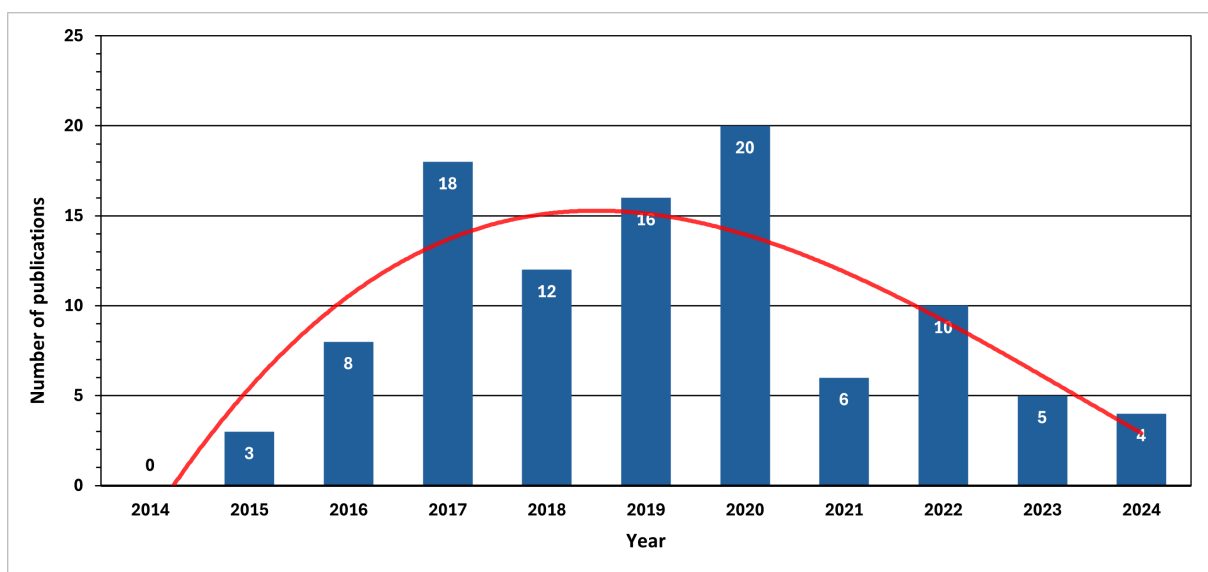


Figure 2.2: Number of papers of the SRL study published each year.

2.3.2 Study participants

As previously mentioned, the electromyographic signals sent by the Myo armband can vary between individuals due to physiological differences. As a result, when using the Myo armband for a specific application, it is generally necessary to ask multiple people to perform the same gestures. In classification and medical studies, a large number of participants is often sought. For example, E. A. Chung et al. [41] involved 120 participants to recognize real-time hand gestures using deep learning

techniques. Other studies focused on robotic applications did not provide the number of participants. In this case, we used the "AVERAGEIF" function to calculate the average number of participants for studies that reported multiple participants. On average, studies involved 18 participants, with a standard deviation of 25. The distribution of papers with participant ranges is depicted in Fig. 2.3. As shown, most studies do not involve more than 20 participants. We can also highlight that there was 337 men and only 188 women involved in those studies (2.4).

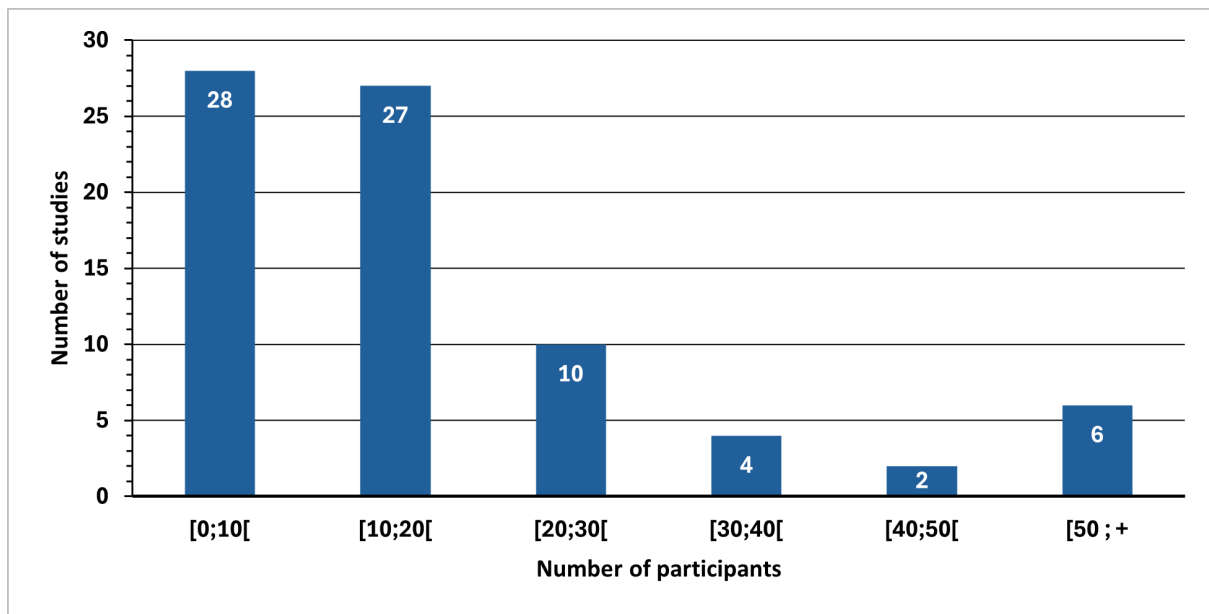


Figure 2.3: Distribution of studies by range of 10 participants.

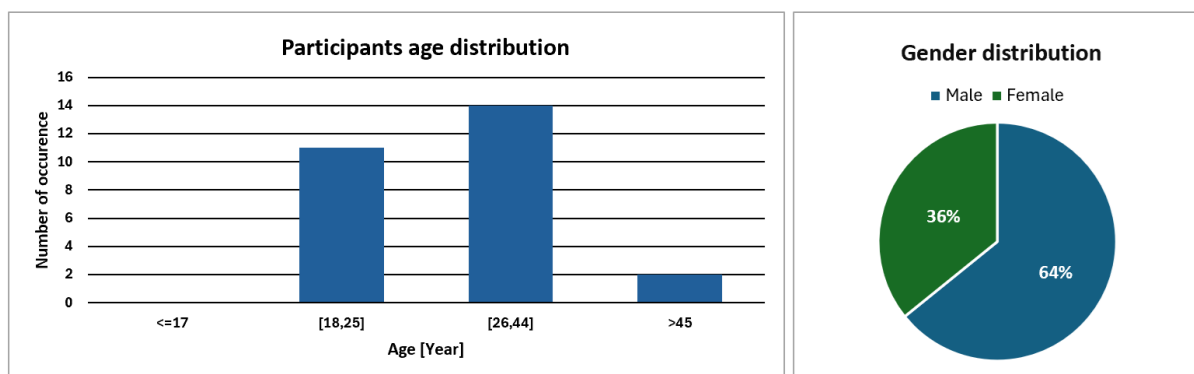


Figure 2.4: Gender and age distribution of participants over all studies, 337 men and 188 women.

2.3.3 Other distinctive observations

We will now present additional relevant observations from these studies. First, we note that the device used most frequently in parallel with the Myo armband is the Leap motion, used in 7 studies, followed by the HTC Vive controller with 3 mentions

(six virtual reality headsets were used in total). The Leap motion is another recognition device, resembling a small camera that can detect finger and hand movements. We also note that the most commonly used software is Matlab, cited in 13 studies as a data analysis tool, but also Unity3D, which allows for the creation of a 3D virtual world, used in 9 studies.

The placement of the Myo armband is also an interesting observation. The Myo was used to be placed on the forearm, but three studies placed it on the upper arm and one study on the calf. We can also note that 5 studies used two Myo armbands per subject, with three of them placing them on both front arms and the other two on the same arm, one on the front arm and the other on the biceps. In total, 92% of myo armbands were placed on the forearm.

Most studies have provided descriptions of the gestures associated with their commands. As gestures can vary widely, we were unable to list them all (especially those from sign languages of different nationalities). More than 30 different gestures were repeated more than once, but 5 gestures recurred more frequently than others (see Fig. 2.5) : 'wave in' and 'wave out' (33% recurrence), 'pinch' (25% recurrence), 'open' with 41% recurrence, and finally 'fist' with 49% recurrence, mentioned in 50 papers. Note that these numbers may be even higher, as some authors did not specify the gestures used in their studies.

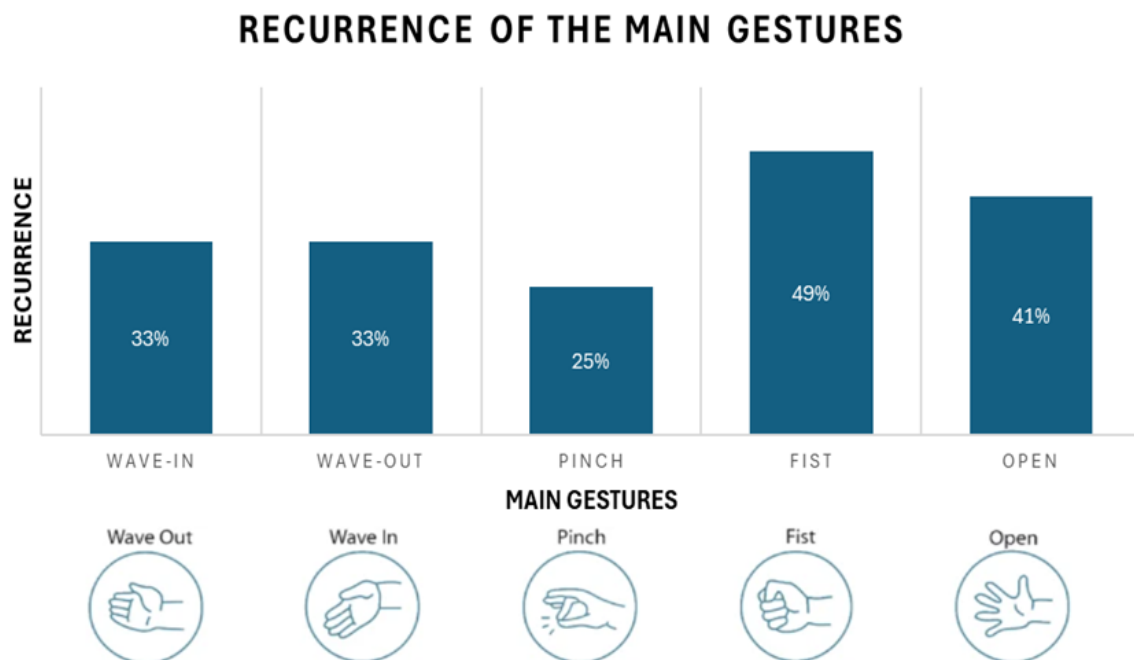


Figure 2.5: Recurrence of the 5 main gestures in the 103 papers.

2.4 Domains of application

As previously mentioned, the application domains of the papers analyzed can be broadly categorized into four main areas: Computational Research, Lifestyle and Recreation, Health Science, and Robotics. As shown in Fig. 2.6, 34 papers fell under the category of Computational Research, 30 papers under Lifestyle and Recreation, 21 papers under Health Science, and 17 papers under Robotics.

FIELDS OF APPLICATION FOR MYO ARMBAND

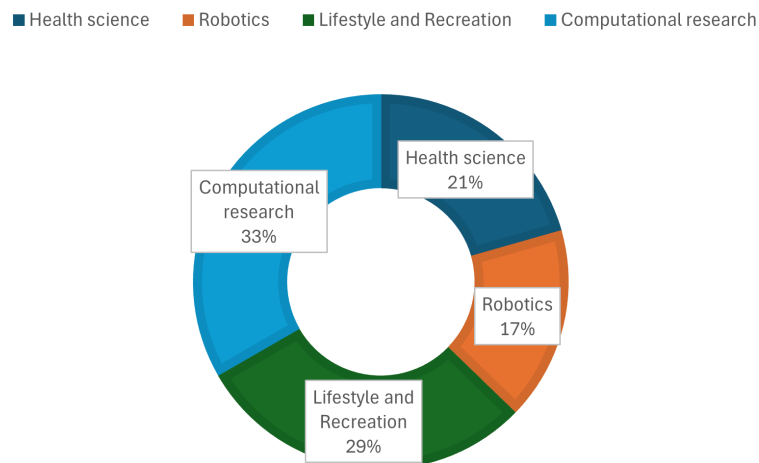


Figure 2.6: Distribution of the papers in the 4 categories of application domain.

In this section, we will delve deeper into each of these four domains, examining the specific research and findings within each area. By doing so, we can gain a more nuanced understanding of the studies and draw concrete conclusions about what is being researched and achieved in each domain.

2.4.1 Health science

As shown in Fig. 2.7, this section is composed of four subcategories. These are presented on the Tab. 2.2.

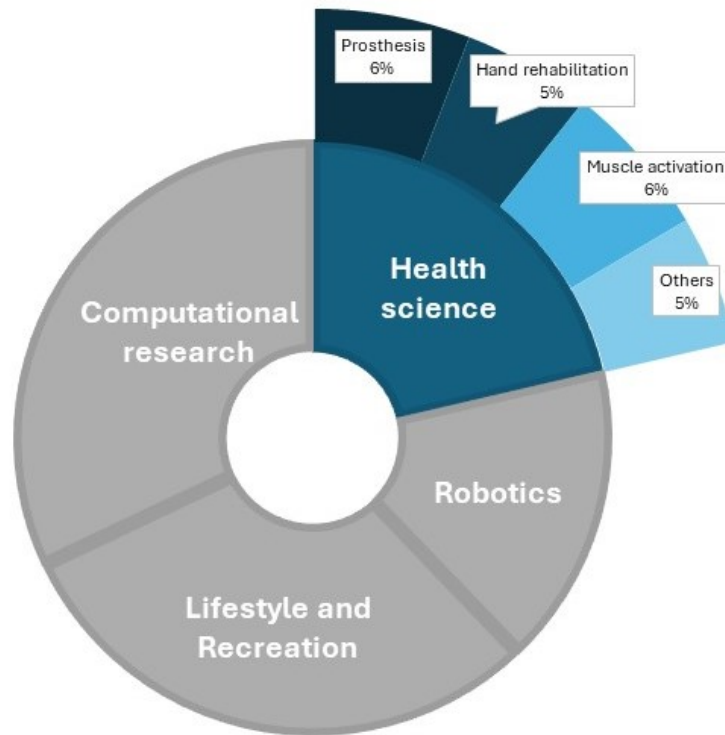


Figure 2.7: Subcategories within the health science field.

It is important to note that this categorization is not entirely objective, as some studies may have multiple objectives or may be subject to interpretation. In medical studies, it is often interesting to simultaneously question both healthy and non-healthy subjects, depending on the study case. For example, in prosthetic studies, it may be useful to include subjects with amputations. In this medical category, we count only two studies that have questioned non-healthy subjects, showing that finding and recruiting subjects with specific medical conditions or diseases can be challenging, which can further complicate the process of conducting research in these areas. 21 of them had Parkinson's disease [27], while one additional subject had an arm injury [50]. In a study unrelated to the medical field, 30 subjects with multiple sclerosis participated in a video game survey [88]. Overall, 15% of participants in medical-themed studies had health conditions compared to 4% in the total corpus.

Table 2.2: Summary of studies related to health science based on the Myo armband.

Category	Prosthesis
Papers	6
Description	Prostheses controlled by the Myo armband, including those for arm, forearm and hand.
Example	M. Arozi et al. [80] present a method to classify the hand gesture to control a prosthetic hand.
References	[17, 18, 80, 90, 110, 123]
Category	Hand rehabilitation
Papers	5
Description	Myo as a tool for hand rehabilitation.
Example	Cascarano et al. [27] used the Myo armband to aid Parkinson's patients with writing difficulties by engaging them in drawing circles. The proposed method has demonstrated promising results, suggesting its clinical usability for diagnosing Parkinson's disease.
References	[27, 100, 115, 146, 151]
Category	Muscle activation
Papers	6
Description	Using sEMG signals from the Myo armband to quantify forearm muscle force and activation.
Example	This approach can facilitate better detection of muscle fatigue compared to alternative methods [117], and lay the groundwork for advanced prostheses [109].
References	[1, 101, 103, 109, 117, 150]
Category	Others
Papers	5
Description	Discuss gesture recognition applications in the medical field.
Example	as exemplified by Sathiyarayanan et al. (2016) [112].
References	[5, 28, 50, 71, 86]

2.4.2 Robotic

Controlling a robot with a Myo Armband offers the advantages of intuitive and natural gesture and motion detection. We have categorized the papers discussing robotics based on the type of robot interacting with the device. They are presented on Tab. 2.3.

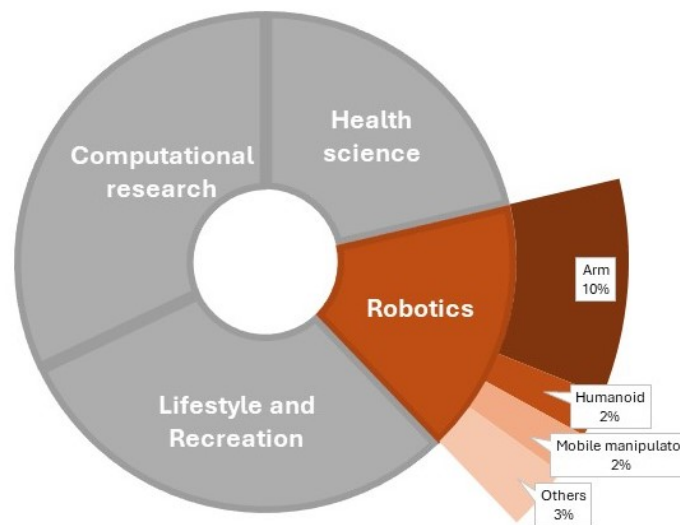


Figure 2.8: Subcategories within the robotics field.

We will also examine the various movements chosen to execute specific commands. The choice of movements is crucial in this category as it must be logical and intuitive for the user to adapt quickly and be productive when using the armband. Among the five basic gestures of the Myo armband (see Fig. 2.5), the fist and open hand movements are the most commonly used for controlling robot movements across all subcategories. In most cases, these hand opening and closing movements serve to activate or deactivate the robot's end effector. Boru et al. [21] and Muhammad et al. [125] use this gesture to open or close the gripper of the arm. In Cruz et al. [33], this gesture is employed to activate a paint gun mounted at the end of the robot arm. To move the robot arm in 3D space, various movements are required due to the robot arms having 6 to 9 degrees of freedom. In these applications, gestures involving the movement of the operator's entire arm are primarily used. For example, Boru et al. [21] uses a Leap Motion device to capture finger movements for controlling the robot. Cruz et al. [33] uses a single Myo armband on the forearm, where forearm movements control one joint of the robot, and "wave in" and "wave out" gestures (see Fig. 2.5) are used to switch the reference joint. The most optimal method appears in three following studies [25, 55, 142], where two Myo armbands are placed on the upper arm and forearm to control the robot arm in three-dimensional space. This allows for more intuitive movement, as the robot arm mimics the operator's arm movements. Despite the Myo armband being originally designed to be worn only on the forearm, these methods show promising results, enabling the tele-robot manipulator to replicate human arm motions and resist both low and high-frequency disturbances.

Table 2.3: Summary of studies related to robotic based on the Myo armband.

Robot type	Manipulator arm
Papers	10
Description	Robotic fixed arm, like UR5 or KUKA iiwa either for industrial purposes or other uses.
Example	Cruz et al. [33] uses the armband to control a UR5 robot arm.
References	[21, 25, 33, 34, 45, 55, 125, 126, 139, 142]
Robot type	Humanoid robot
Papers	2
Description	Humanoid robot designed to communicate with us.
Example	Kobylarz et al. (2020) [72] interacted with a human-like robot using the Myo armband to convey "yes" or "no" commands.
References	[12, 72]
Robot type	Mobile manipulator
Papers	2
Description	Robot that is both capable of manipulation and mobility.
Example	In Nogales et al. (2022) [106], the KUKA youBot, a mobile arm on wheels, was controlled.
References	[106, 141]
Robot type	Others
Papers	3
Description	Other non-classified robots.
Example	Such as a camera system equipped with servo motors, which moved with three arm gestures as described in Patel et al. [7].
References	[7, 91, 147]

2.4.3 Lifestyle and Recreation

In this section, we explore applications related to daily activities, hobbies, and games. The various subcategories identified are extensive and are presented in Tab. 2.4 and Tab. 2.5.

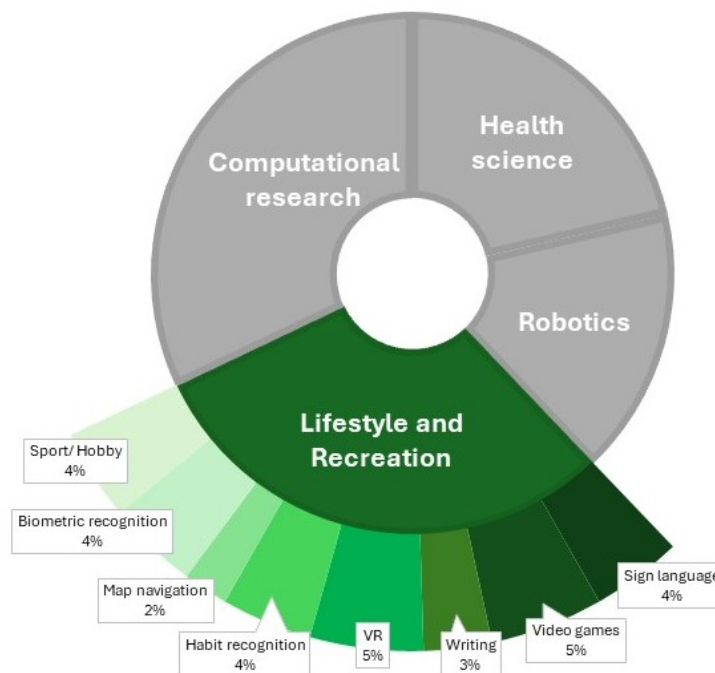


Figure 2.9: Subcategories within the lifestyle and recreation field.

Regarding biometric recognition, it's notable that electromyographic signals have been proven to be unique physiological characteristics of the human body, akin to fingerprints or facial features widely used today. This intriguing application of the Myo armband is worth exploring. B. Fan et al. [16] allows subjects to be able to unlock their phones by simply picking them up from a table, achieving a verification accuracy of 91.81%. L. Lu et al. [74] attained a verification accuracy of 99.26% with a hand-open gesture. Both studies utilized a Siamese neural network. Zadeh et al. [149] used finger pinching and achieved an average task completion success rate of 95% with a Fastforward neural network. Although Tepe et al. [121] did not provide concrete results, it, along with the findings of the other three papers, demonstrates that the Myo armband offers a modern and viable approach to biometric recognition.

Table 2.4: Summary of studies related to lifestyle and recreation based on the Myo armband. (Part A)

Category	Sign language
Papers	4
Description	Myo armband as a tool to recognize hand gestures of sign languages.
Example	G. Marquez et al. [40] states that the MYO armband can be used successfully in recognition of Turkish Sign Language.
References	[40, 70, 84, 127]
Category	Video games
Papers	5
Description	Papers discussing the use of the Myo armband as a controller for video games.
Example	Salichs et al. [114] used the Myo in a cooking video game.
References	[4, 19, 88, 114, 140]
Category	Writing
Papers	3
Description	Myo armband used as an assistance for hand and keyboard writing.
Example	Qiu et al. [46] used it to write on a computer keyboard.
References	[39, 46, 118]
Category	Virtual Reality (VR)
Papers	4
Description	Research investigating the Myo armband's applications in virtual reality environments.
Example	Chen et al. [48] used the Myo as an input and output to handle objects in Virtual reality.
References	[20, 36, 37, 48]
Category	Habit recognition
Papers	4
Description	Studies focusing on recognizing gestures or movements in daily life situations.
Example	Chen et al. [29] used the Myo armband to recognize smoking among other habitual gestures like drinking.
References	[29, 44, 76, 85]

Table 2.5: Summary of studies related to lifestyle and recreation based on the Myo armband. (Part B)

Category	Map navigation
Papers	2
Description	Research discussing map navigation using the Myo armband, allowing users to zoom and navigate on virtual maps.
Example	Sathiyarayanan et al. [111] used the Myo to navigate on Apple maps.
References	[92, 111]
Category	Biometric recognition
Papers	4
Description	Papers addressing biometric recognition using the Myo armband.
Example	L. Lu et al. [74] shows that Myo enables users to unlock smartphones using specific gestures, leveraging electromyographic signals.
References	[16, 74, 121, 149]
Category	Sports and hobbies
Papers	4
Description	Research focusing on using the Myo armband in sports, hobbies, or cultural activities.
Example	A. Raina et al. [8] used the Myo to analyze the gesture of a professional badminton player.
References	[8, 59, 66, 104]

2.4.4 Computational research

The computational research regroupes 3 subcategories :

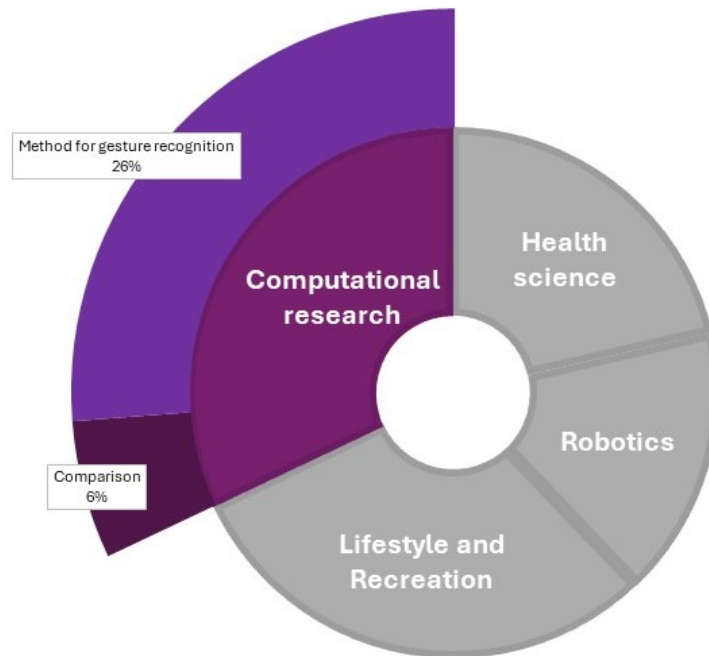


Figure 2.10: Subcategories within the computational research field.

When signals are processed, an algorithm classifies them based on their original movement. When signals are processed, an algorithm classifies them based on their original movement. These algorithms can vary in nature, including neural networks, regressions, and other methods. In this section, we will explore the different algorithms used and their frequency of use in processing signals from the Myo armband throughout the corpus. As shown in Fig. 2.11, neural networks are the most widely used, representing 38% of the studies. Specifically, convolutional neural networks (CNN) and feedforward neural networks (FFN) are the most commonly used, among more than seven types of neural networks used. Support vector machines (SVM) follow with a frequency of 24%, these supervised methods being used for classification, regression, and anomaly detection. The last third of algorithms includes methods such as K-nearest neighbors and principal component analysis. These data provide a quantitative idea of the effectiveness of the algorithms used, but not a qualitative one, which is not within the scope of this study.

Table 2.6: Summary of studies related to computational researches based on the Myo armband.

Category	Gesture recognition methods
Papers	27
Description	Studies focused on specific methods or algorithms for recognizing different gestures made with the Myo armband. The primary objective lies in assessing the validity of the proposed method/algorithm.
Example	Tepe et al. [123] compared 3 classifiers to correctly classify 6 finger gestures, using both the sEMG and gyroscopic signal of the Myo armband.
References	[2, 3, 13, 15, 22, 41, 51, 54, 56, 57, 61, 62, 64, 69, 79, 81–83, 99, 107, 116, 119, 123, 131, 132, 145, 148]
Category	Comparative studies
Papers	6
Description	The validity of the Myo armband is evaluated or compared with other devices.
Example	Mendez et al. [89] compared the error of the sEMG between the Myo armband and a conventional EMG acquisition system (CONV) that captures the full EMG spectrum.
References	[6, 26, 35, 65, 89, 122]

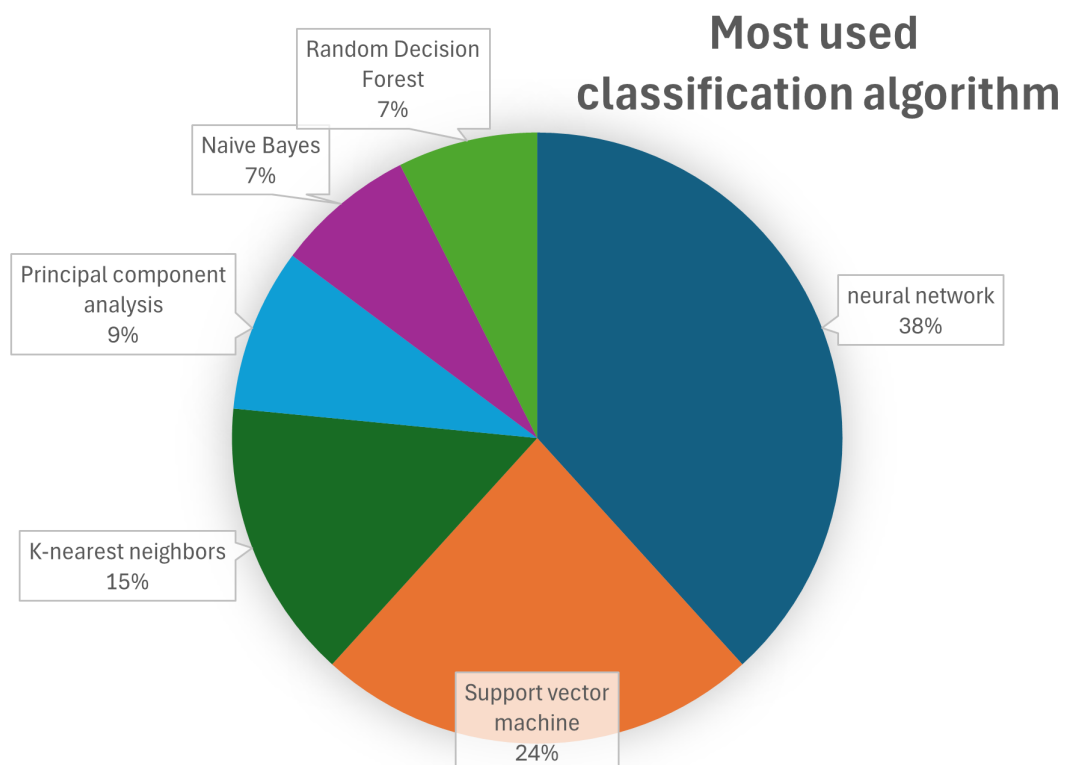


Figure 2.11: Most frequent classification algorithms used in the 103 papers of the SRL.

According to Mendez et al. [89], the effectiveness of the Myo armband is assessed in comparison to a conventional EMG acquisition system (CONV). It suggests that while the bandwidth of the Myo armband is limited ($<100\text{Hz}$), this is not necessarily a drawback in movement detection but rather limits its sensitivity to specific hand gestures. The study concludes that the Myo armband is recommended as a suitable acquisition system for pattern recognition applications.

D. Sueaseenak et al. [35] concludes that the Myo Armband demonstrates high potential, robustness, and comfort in EMG signal acquisition, surpassing the conventional EMG system (BIOPAC) in terms of signal distortion, signal-to-noise ratio, and class-separability. Comparisons with other devices indicate that the Myo armband remains a reference in electromyography due to its ease of use with surface electrodes and sufficient sensor precision.

2.5 Conclusion

In this chapter, through a rigorous methodology, we conducted a systematic literature review on the Thalmic Myo armband. Through this process, we identified 103 studies across 5 database searches addressing our research question: *"What are the diverse applications of the Myo armband ?"*. This encompassed over 30 common gestures, with more than 27 different classification algorithms, alongside hundreds of other gestures utilized in single studies (such as sign language, etc). A total of 1286 subjects participated in experiments spanning 4 application domains and 18 sub-categories (see Fig. 2.12). Despite the decline in the number of papers following the discontinuation of the Myo armband's commercialization in 2018, studies continue to be presented, indicating ongoing interest in this technology, thanks to the comfortable combination of its 8 surface electromyographic sensors and its 9-axis IMU, proving that the Myo armband is not yet obsolete.

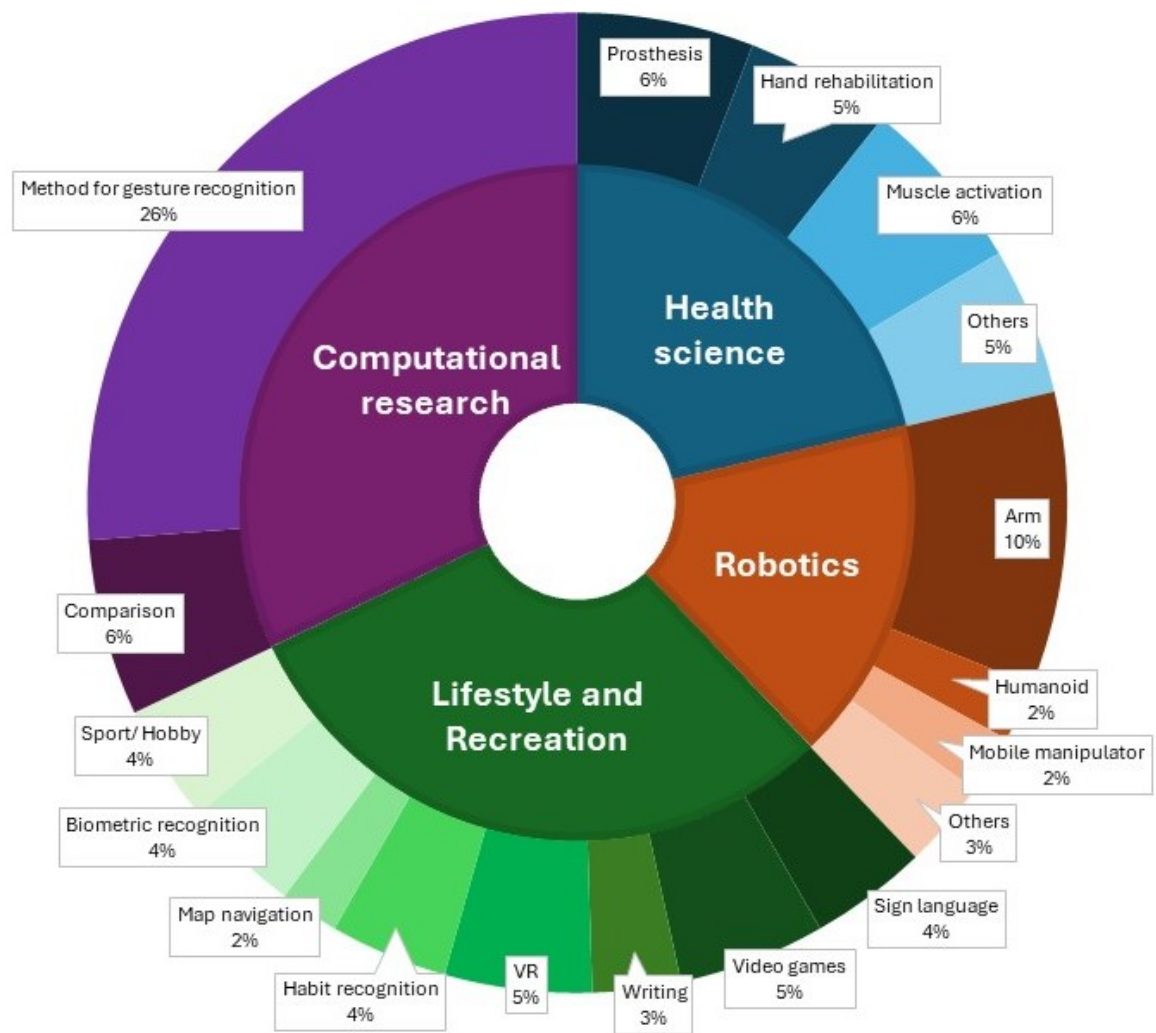


Figure 2.12: Distribution of the papers in the categories of application domain.

While exploring the various application domains of the Myo armband, we discovered that it can serve equally well in medical studies, smartphone unlocking, and robot control. Although classification may sometimes be subjective due to differences between the study's primary objective and the application undertaken, this systematic study provides an insightful overview of current and potential applications of this device.

ELICITATION STUDY

3.1 Introduction

Elicitation studies are used to inform the designers of their potential end-users' abilities and preferences before committing to a build based on the making of an inventory of parameters and values supplied to the user [11].

As Ajzen & Fishbein stated (1980) stated :

“ The purpose of an elicitation study is to determine the behavioral, normative, and control beliefs of a population, and to obtain substantive information about the cognitive foundation of people's behavior. ”

More specifically, this chapter will carry on an elicitation study based on the analysis and observations of the participants behavior in a given setting (see Sec. 3.2.1) and within a given situation, while performing some assigned tasks (see Sec. 3.2.3) while using the Thalmic Myo armband. Following the study and the discussion of its results, a catalogue of gestures related to the application is finally dressed.

3.2 General experimental design

The practical situation of the elicitation study performed in this work is about handling phone's functionalities while biking without directly interacting with the phone itself. The main motivation here is to allow the user to control its phone and to be constantly aware of its environment at the same time.

Note that this study will not focus on the implementation of any gestures within the software of the armband. The aim here is to provide the most suitable gestures for each commands presented in Sec. 3.2.3. However, external people to Thalmic Labs, the manufacturer of the armband, have done such implementations where the third party codes have been regrouped on the following GitHub repository.

3.2.1 Design and procedures

For each participant, the elicitation study took place in the same working room where the experimental setup is shown on Fig. 3.1. The procedures of the experiment, being also the same for each participant, are presented hereunder.

Step 1 The participant is welcomed to the setup by the experimenter and is asked to sign a consent form stipulating that he could stop the experiment at any moment by notifying the experimenter without any consequence, and that their data would only be processed and used for scientific purposes in a strictly confidential manner¹. For privacy concerns, an anonymous identifier, represented by the letter *P*, is assigned to each participant and all videos recorded during the experiment avoided their faces by focusing only on their arms, as shown on Fig. 3.1. The consent form is available in Appendix A.

Step 2 The participant is also asked to complete a sociodemographic questionnaire (e.g., age, gender, handedness, studies). Furthermore, based on a 7-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree, the participant had to estimate their usage frequency of phones, tablets, computers, connected objects, biking and the Thalmic Myo armband in the case of prior knowledge of the device. The questionnaire is available in Appendix A.

Step 3 Before starting the experiment, a quick introduction is given to the participant by the experimenter. This introduction included a presentation of the Thalmic Myo armband with its functionalities and limitations followed by an explanation of this study's test case and its course.

¹In accordance with the UCLouvain's privacy and the General Data Protection Regulation (GDPR).

Step 4 During the experiment, slides displaying the different referents (see Sec. 3.2.3) are shown to the participant, these slides are at disposal in Appendix B. As the participant see the referent, a chronometer is started and stopped when a suitable gesture is found. Then, the participant is asked to give a rating regarding the goodness of fit and the complexity² of its gesture, on a scale from one to seven. This step is repeated for each of the fifteen referents.

Step 5 At the end of the experiment, the participant is asked to give a feedback of its experience with the Thalmic Myo armband by rating eight affirmations, once more on a scale from one to seven with the Likert system.

Step 6 The slides displaying the referents are randomized for the next participant.

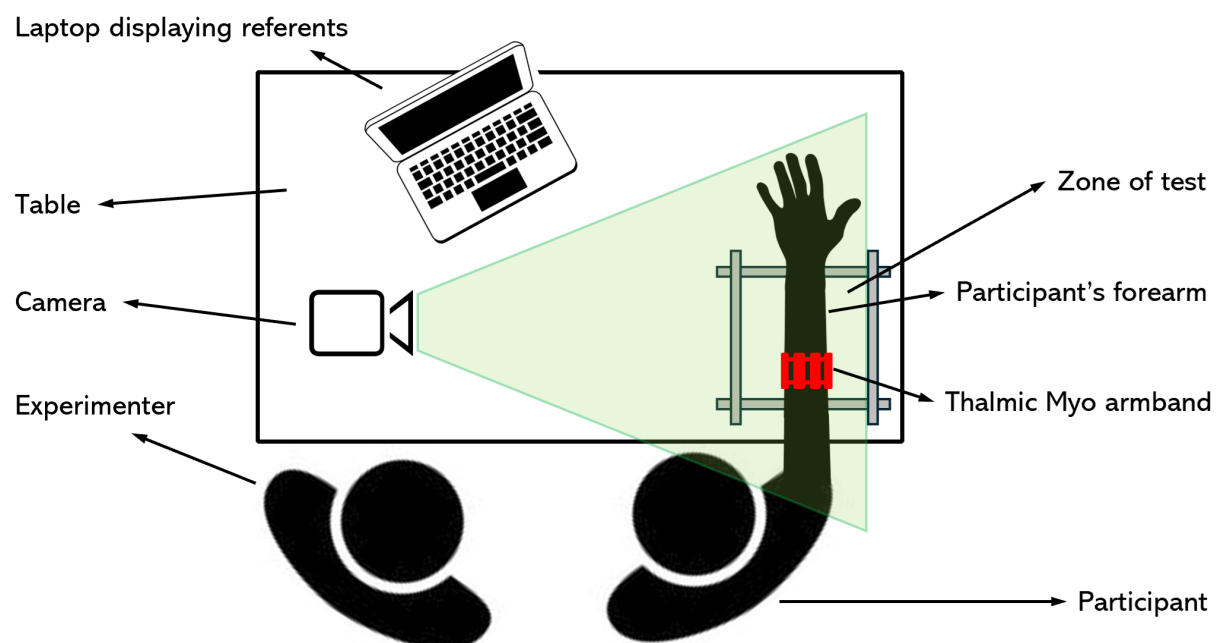


Figure 3.1: Experimental setup of the elicitation study.

Finally, when the elicitation study is over, records of all gestures performed by the participants for a given referent are regrouped into a single file. This method aims at facilitating the processing and classification of the gestures made in Sec. 3.3.1.

3.2.2 Participants

For this elicitation study, twenty-five non-paid people aged from 20 to 28 years old participated to the experiment where the gender parity is shown on Fig. 3.2. Among

²The rating of the gesture's complexity is based on the situation where the participant is riding a bike. Therefore, this rating is purely subjective as a person's comfort to do gestures on a bike differs from one to another.

these participants, 96% are still students in various domains related to human sciences (psychology, communication, sociology...) and exact sciences (civil engineer, bio-engineer...) and the other 4% are young graduates. Twenty-three participants were right-handed, two participants were left-handed and none reported having dexterity problems or any handicap.

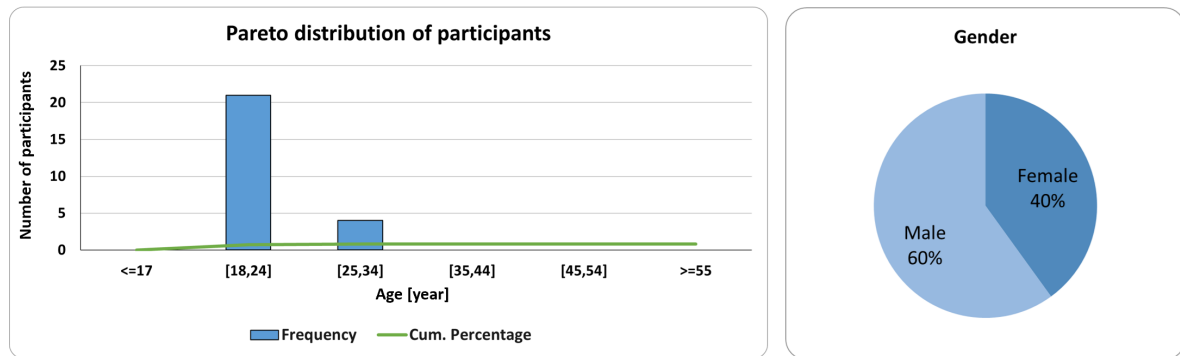


Figure 3.2: Pareto and gender distributions among the different participants.

As mentioned in Sec. 3.2.1, the participant had to estimate, on a scale from one to seven, their usage frequency of several types of devices, of a bike and also the Thalmic Myo armband in case of prior knowledge of the device. As we can see on Fig. 3.3, the usage of a bike is spread on the different levels allowing a good representation of the bike's ease of use among the participants. Finally, while the level of use of computers and smartphone is the highest, no participants ever manipulated the Thalmic Myo armband, and only two have heard of it before. All these data, with the gestures from the study itself, are regrouped in the spreadsheets in Appendix C.

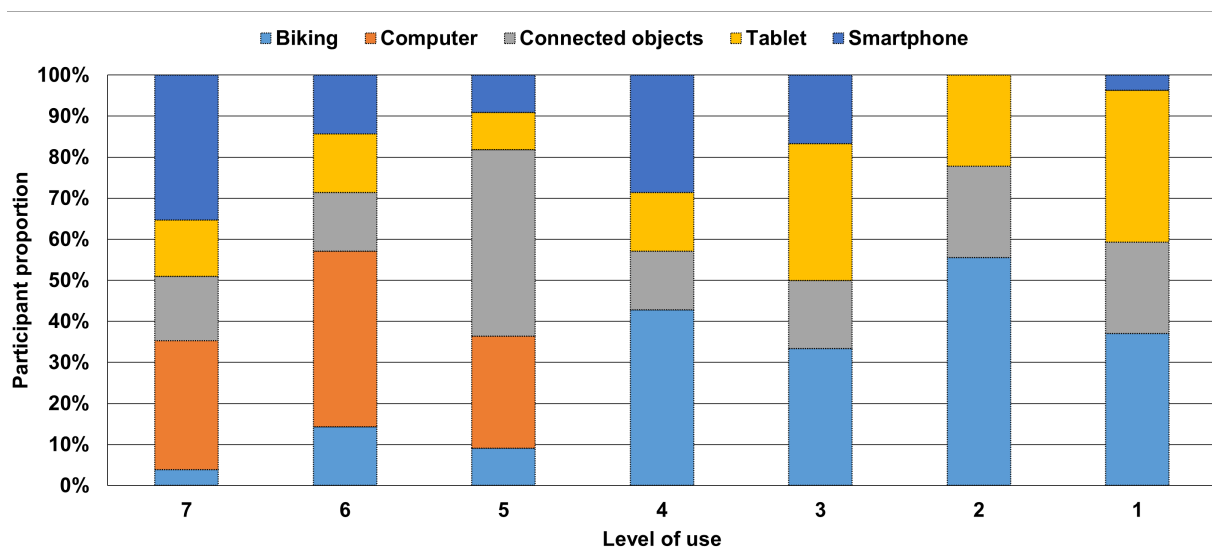


Figure 3.3: Results of the demographic study among the participant about their usage frequency of different types of devices.

3.2.3 Task

The experimental setup employed fifteen referents to be interpreted, these referents are listed in Tab. 3.1 and are regrouped in the set of all referents R . While half of them, from R1 to R9, are functionalities that are already implemented either directly on the phone or in an application like *Strava*, the other commands are purely fictive and have been imagined in the scope of this study. The latter are described bellow.

Table 3.1: Set of referents, with their related identifiers, that had to be interpreted by all the participants during the elicitation study.

ID	Referent
R1	Turning on <i>Do Not Disturb</i> mode
R2	Turning off <i>Do Not Disturb</i> mode
R3	Sending a predefined reply
R4	Emergency call
R5	Starting a route (<i>Strava</i>)
R6	Ending a route (<i>Strava</i>)
R7	Starting a chronometer
R8	Ending a chronometer
R9	Making a lap
R10	Turning on performance status
R11	Turning off performance status
R12	Turning on front and back lights
R13	Turning off front and back lights
R14	Turning on bad weather alerts
R15	Turning off bad weather alerts

The referents R12 and R13 are quiet straight-forward to understand but require front and back lights that could connect and to be controlled by a smartphone linked to the Thalmic Myo armband, through an application for example. On the other hand, referents R10, R11, R14 and R15 are commands that do not currently exist but that could be directly implemented on the phone itself. In fact, the commands R14 and R15 could be implemented on the weather application where their purpose would be to warn the user, through vibrations of the armband, if he will encounter any severe weather on its way (rain, strong winds, lightnings, etc.) given its current position, speed and direction. Finally, R10 and R11 are commands that could be added to *Strava* and which are closely related to the already existing lap functionality. These two commands aim at giving a feedback to the user whether his performances on the lap he just finished were better or worse than the ones for the predeceasing lap, with

continuous and pulsated vibrations, respectively.

Note that due to the law and security concerns, some commands have been voluntarily put aside in this study. Indeed, given the fact that a bike is considered as much a vehicle as a car, the cyclist must follow the same rules regarding the phone usage on the public roads. Therefore, no commands related to calls functionalities (e.g. answering to a call) have been considered, except for emergency calls. Furthermore, for obvious security reasons, wearing headphones is not recommended thus excluding any commands related to music monitoring (e.g. increasing or lowering the volume).

3.3 Post-processing and results of the study

3.3.1 Gesture's classification

At the end of the elicitation study, the 375 videos related to the 15 gestures performed by the 25 participants have been sorted within separate files corresponding to each gesture allowing an easier classification. This process of classification was composed of two major phases as explained in what follows.

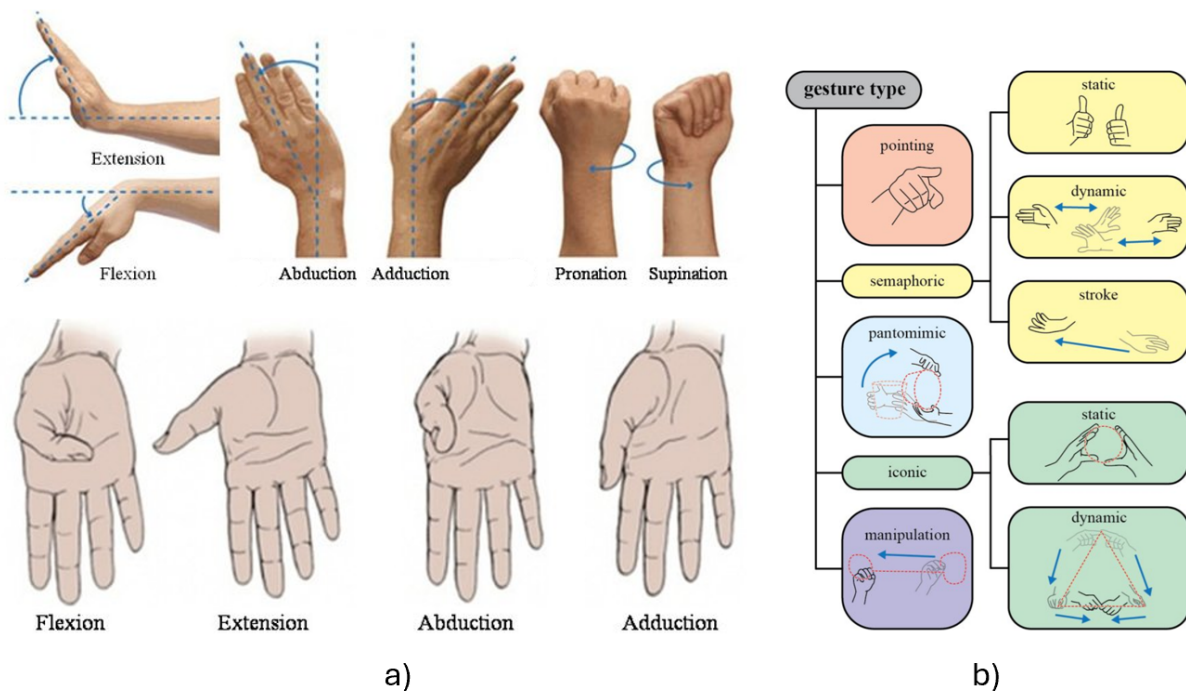


Figure 3.4: a) Representations of the types of movements used for the descriptions of the participants' gestures, image taken from [38]. b) Natures of underlying meanings of a gesture used for the final classification.

The first phase consisted of the mechanical description of the gestures. In fact, almost all gestures were combination or the same as the gestures depicted in Fig. 3.4a. Furthermore, in order to have a more precise description of the movements, spatial and quantification information have also been added. Then, for example, two gestures based on a flexion of the wrist can be spatially differentiated by the orientation of the flexion (e.g. to the top or to the left). The same idea is applied to any pronations and supinations of the wrist where, for example, two pronations can be quantitatively distinguished by their amplitudes (e.g. a pronation of 90° or a pronation of 180° will be different).

The second and final phase aimed at obtaining the different classes of gestures based on their underlying meanings or, in other words, their nature (see Fig. 3.4b). In that scope, five natures of movements have been highlighted :

1. **Semaphoric** : hand postures and movements conveying specific meanings.
2. **Deictic** : pointing gestures that indicate people, objects, or directions.
3. **Pantomimic** : gestures that demonstrate a specific task to be performed or imitated, which mostly involves motion and particular hand postures.
4. **Iconic** : gestures communicating information about objects or entities, such as specific sizes, shapes, and motion paths.
5. **Abstract** : all gestures that could not be classified in the previously mentioned categories.

Following these natures of movements, the 375 gestures have been regrouped into twenty-five categories, as shown in Tab. 3.2, where categories are listed according to their corresponding nature and are identified with the capital letter C . It is important to underline that the majority of the gestures have been classified based on their physical description and not on the intuitive meaning they convey. For example, the category 30 represents the raining movement that some participants did with their fingers and not the action of typing on a keyboard.

Table 3.2: Categories used for the classification of the 375 gestures obtained from the elicitation study, with their related identifiers and nature.

Nature	ID	Description
Deictic	C10	Pointing a direction with the index/fingers
Semaphoric	C20	Swiping to the right
	C21	Swiping to the left
	C22	Swiping to the top
	C23	Swiping to the bottom
	C24	Thumbs up
	C25	Thumbs down
	C26	Slicing to the left
	C27	Slicing to the right
	C28	Rotating the wrist clockwise
	C29	Rotating the wrist counterclockwise
Pantomimic	C30	Typing on a virtual keyboard
	C31	Pushing on a button with the index
	C32	Pressing chronometer button
	C33	Swiping on a phone's screen
Iconic	C40	Drawing a circle with the hand or the index
	C41	Imitating a phone with the fingers
Abstract	C50	Opening the hand
	C51	Closing the hand
	C52	Snapping fingers
	C53	Pinching any fingers with the thumb
	C54	Flexing fingers
	C55	Extending fingers
	C56	Waving the hand with the palm facing down
	C57	Clapping hands

3.3.2 Results and discussion

Once every movement has been classified, some majors results revealed themselves and are presented in what follows.

3.3.2.1 Nature of the gestures

Concerning the different gesture's natures, we can observe on Fig. 3.5 that the abstract and semaphoric ones are the most redundant. In fact, regarding the semaphoric nature, many participants performed primitive gestures where only the wrist was put in action (swipes and rotations) without any special meaning with respect to the referent itself. The same outcomes have been seen for the abstract nature where only pinching movements with different fingers for different referents were often used. It is thought that the reason behind this behavior relies on the degree of intuitiveness that each referent conveys among the participants. Indeed, it would be easier to perform a more complex or specific movement for a task that would appear more natural to us (e.g. imitating a phone with the hand for R4). On the contrary, participants were prone to perform basic gestures for referents they qualified as "unusual" (e.g. Turning on/off performance status).

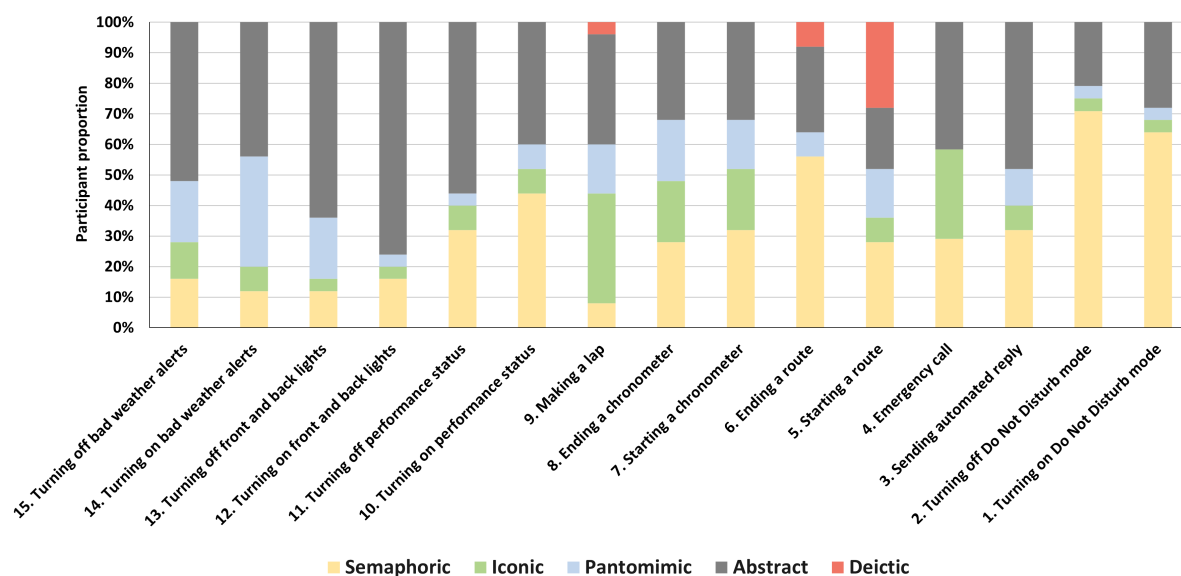


Figure 3.5: Distribution of gestures per nature, color scheme taken from Fig. 3.4b.

This idea is reinforced when we look at the distribution of the iconic, deictic and pantomimic gesture's natures across the referents. One can notice that these natures are more frequent for referents that can be represented through more natural movements. For example, if we consider the referent R9 and R4, most of the participants were drawing a circle with their index and imitating a phone with their fingers, respectively. For the referent R5, mainly represented by the deictic nature, a common movement was to point a direction with the hand opened or with the index. Finally, the pantomimic nature has been especially seen for the referent R14 where

the participants were imitating the falling rain with their fingers, a movement that, as mentioned before, has been physically identified as someone typing on a keyboard.

3.3.2.2 Nature vs. Agreement

As it has been discussed just before, a link between the tasks asked to the participants (i.e. the referents) and the nature of their gesture can be observed. *But do tasks also influence people's tendency to perform the exact same gestures as others ?*

To answer this question, the agreement scores (AS_r) for each referent have been calculated through AGATe [128]. These agreement scores reflect, in a single number, the degree of consensus among participants for a given referent and can be computed as follows [136] :

$$AS = \frac{1}{R} \sum_{r \in R} AS_r \quad \text{with} \quad AS_r = \sum_{P_i \subseteq P_r} \left(\frac{P_i}{P_r} \right)^2, \quad (3.1)$$

where r is a referent in the set of all referents R (see Tab. 3.1), P_r is the set of proposed gestures for referent r , and P_i is a subset of identical gestures from P_r . Hence, the range for AS is $[|P_r|^{-1}, 1]$. For example, referent R12 can be separated into 4 groups of identical gestures : C20, C50, C55, C56 (see Tab. 3.2) such that $P_{20} = 2$, $P_{50} = 16$, $P_{55} = 2$ and $P_{56} = 2$, leading to :

$$AS_{R12} = 3 \times \left(\frac{2}{25} \right)^2 + \left(\frac{16}{25} \right)^2 = 0.4288 \simeq 0.429. \quad (3.2)$$

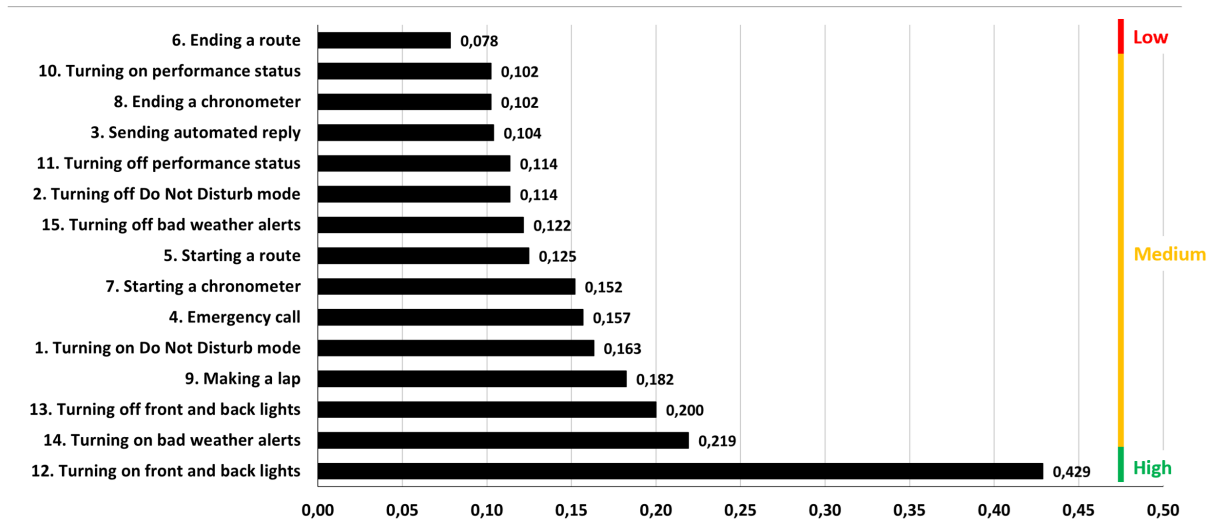


Figure 3.6: Referents in decreasing order of Agreement Score.

By applying this logic to all referents, we end up with the results shown on Fig. 3.6.

Note that, for a given referent, a group containing only one category must be excluded as it is not in agreement with anything else for that particular referent. The global agreement score is obtained by averaging the referent's agreement scores, then giving us a value of $AS = 0.164$.

As we can see on Fig. 3.6, referents represented by gestures of pantomimic and iconic natures are the subject of the highest score value (R4, R9 and R14). This result suggests that people have the same way of thinking when it comes to referents that can be performed through intuitive movements, such as drawing shapes with the index or doing actions with virtual objects. However, the referent with the highest agreement score owe is place to the gesture C50 "*Opening the hand*" within the abstract category (see Tab. 3.2), a result that seems to go in contradiction with what has been said above. One possible explanation could be the underlying meaning behind the hand opening which could be translated as "the diffusion of light beams". Nevertheless, this gesture has been considered as abstract as only the physical description of the movement were used for classification.

3.3.2.3 Correlations between data

While the discussion of two previous sections focused on the natures of the gestures and their impact on the agreement scores, this last section will aim at comparing the agreement score with the averaged Time of Thinking, the Goodness of Fit and the Ease to Perform, for each referent. In sight of facilitating the comparisons, these data have been scaled to the agreement score by normalizing them (i.e. data of the Goodness of Fit and Ease to Perform were divided by 7 and the Time of Thinking data were divided by the largest averaged time encountered). The obtained results are shown on Fig. 3.7.

As we can see on Fig. 3.7a, there is no real correlation existing between the agreement score and the Time of Thinking. Nevertheless, the fact that the correlation value is negative is something that we could have expected. Indeed, as it has been discussed before, intuitive movements are signs of high agreement scores, but they also should theoretically produce shorter time of reflection. Therefore, the correlation factor should tend to -1 as referents with high agreement scores would induce lower time of thinking. However, in this study, this behavior can only be observed for the referent R9 and, to a lesser extent, for referent R12 .

On the other hand, the curves for the agreement scores and the Goodness of Fit seem to follow each other, resulting in a relatively good correlation factor and a result which is consistent with the assumption of an existing relation between the agreement scores and the intuitive gestures. As a matter of facts, participants tended to give

higher ratings in the movements' Goodness of Fitting they judged more "natural", as they thought other people could do the same ones. Finally, one can notice a lower correlation between the Ease to Perform and the agreement scores. The reason behind it could be the fact that this rating is really subjective as it depends on the comfort of people to release the bike handlebars and to perform the gestures.

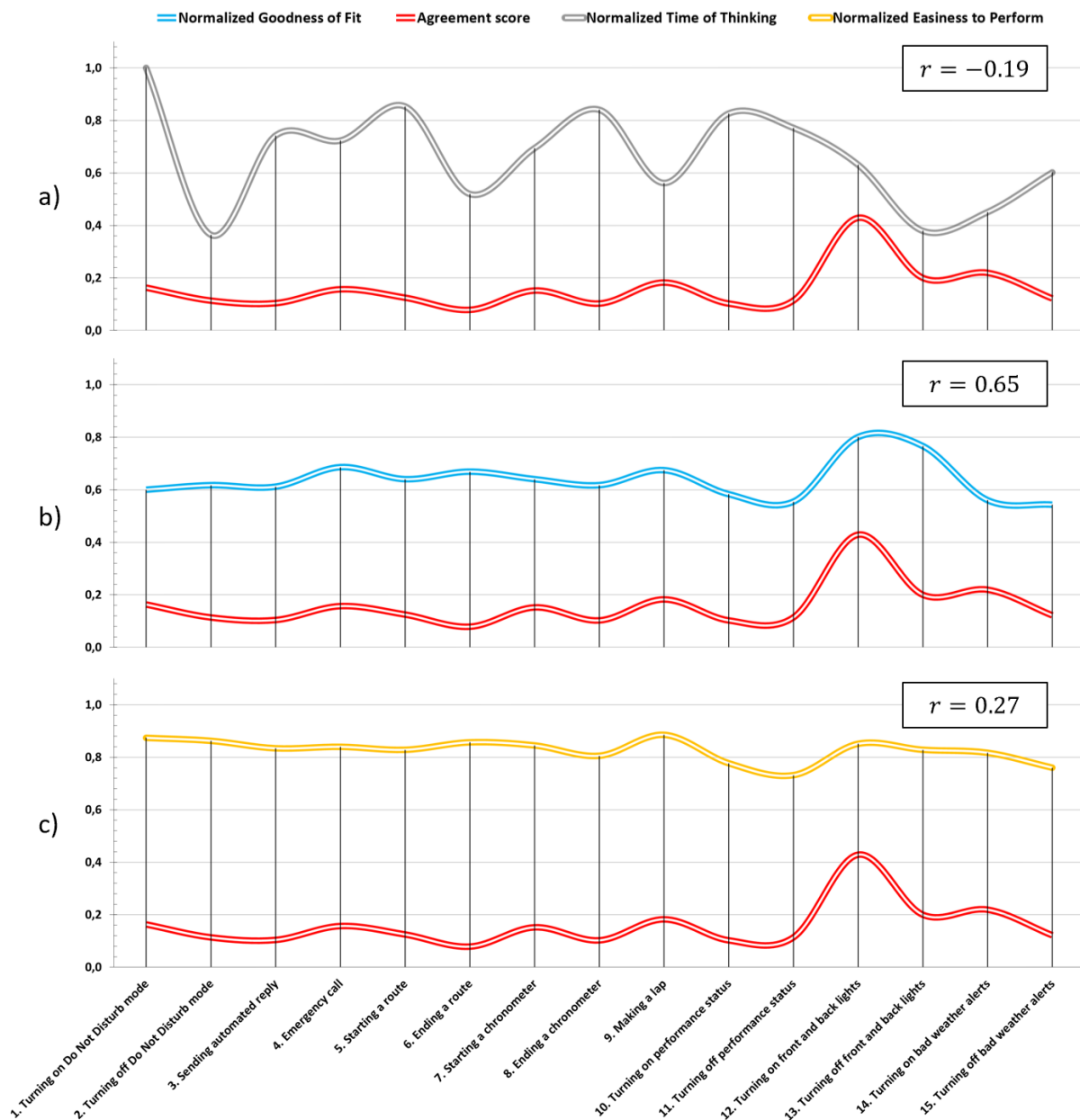


Figure 3.7: Comparison between the Agreement Scores of each referent with their corresponding averaged and normalized a) Time for Thinking, b) Average Goodness of Fit and c) Ease to Perform, with their correlation coefficients r .

3.4 Conclusion

In this chapter, an elicitation study related to the Myo armband from Thalmic Labs has been proposed. The application carried on the handling of some phones functionalities while biking without interacting with the phone directly, allowing the user to focus on its environment.

At first, the steps and the experimental setup constituting the framework of the study has been presented. Once the study finished, the main demographic data related to the participants were given and then followed by the procedures used to classify their movements. The last part of this chapter consisted in a discussion of the obtained results. In that purpose, several data were compared with one another to understand the underlying meanings behind the participant's gestures.

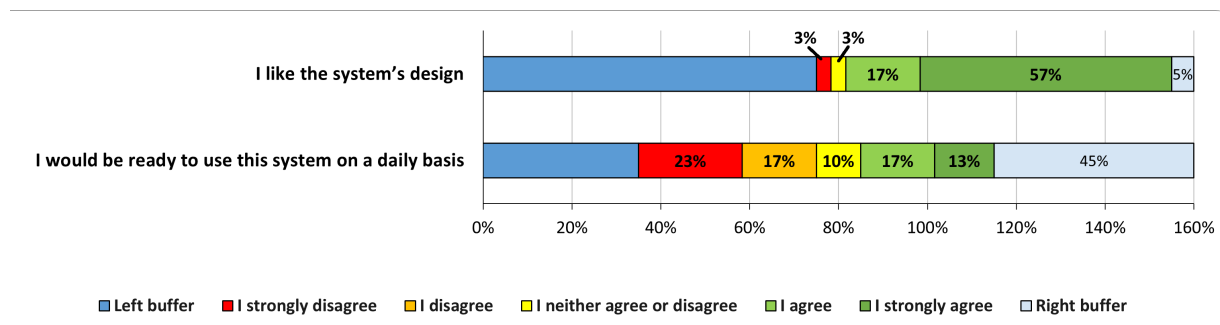


Figure 3.8: Ratings among the participants regarding their global appreciation of the Thalmic Myo armband, in its design and hypothetical usage.

Given the fact the application has not yet been implemented in the Myo armband, the participants were also asked to rate their hypothetical willingness of using the device as well as their appreciation of the device's design. Their ratings are displayed on Fig. 3.8. As we can see, the majority liked the design of the product but there were less enthusiasm about the usage of the device while biking. Most of the feedback from participants mentioned the bulkiness of the device when carried on the forearm, especially when thermal clothes are worn. Others were also concerned about the feeling of discomfort due to the pressure of the armband on the forearm.

Finally, the catalogue of the gestures that could be implemented in the armband are shown on Fig. 3.9. This catalogue was build with respect to the agreement scores of each gestures while avoiding conflicts in case of multiple gestures for a single referent. To do so, the three gestures with the highest agreement scores (AS) for each referent were selected. If several distinct referent are competing for the same gesture, the referent with the highest AS for that gesture wins. For the other referents, the gesture with the second highest score is taken and compared once again with the others in the same way. Then, this process is repeated for each referent. Thereby, one finally

obtains the best fit between a referent and a gesture according to the elicitation study while avoiding any conflict.

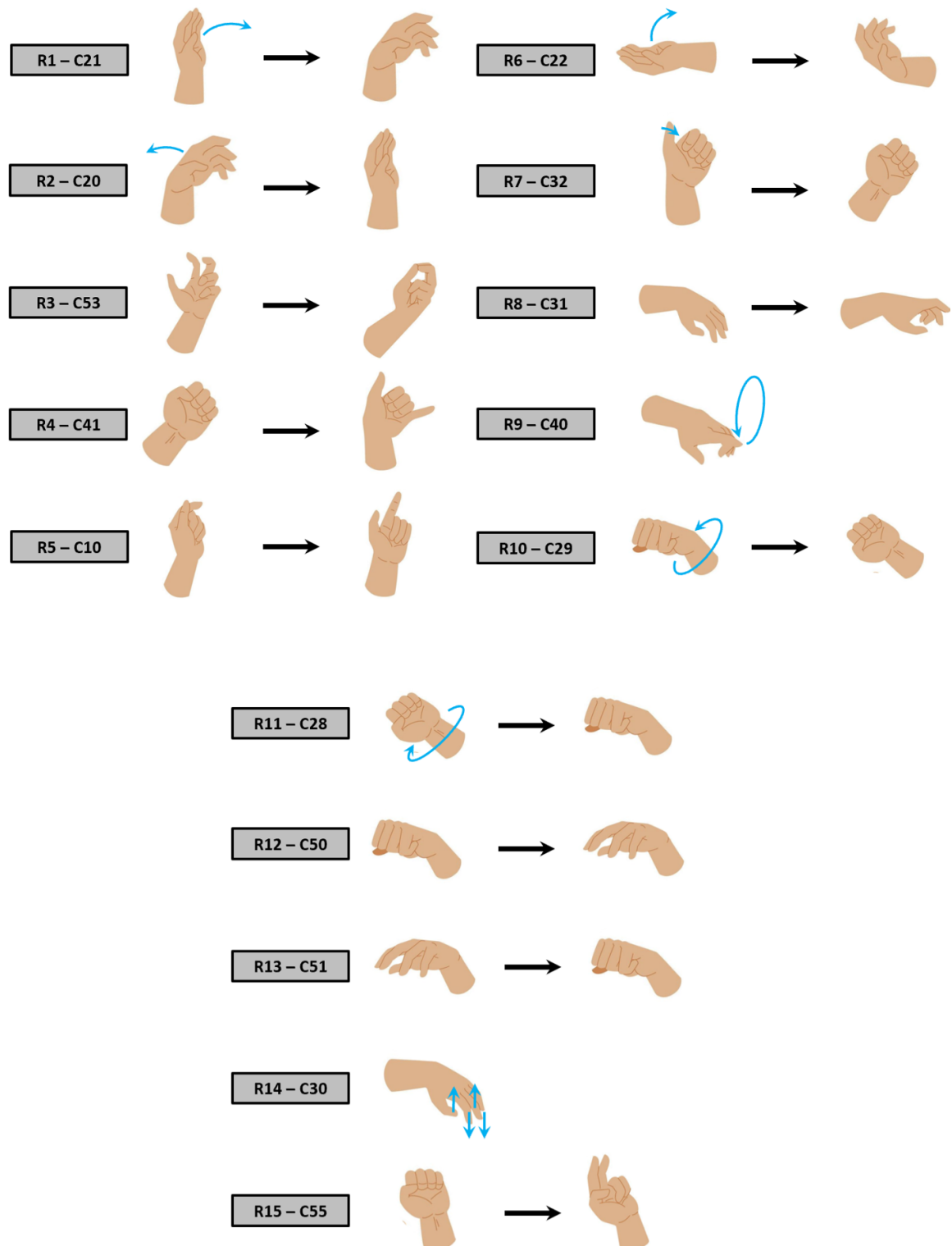


Figure 3.9: Catalogue of gestures resulting from the elicitation study. On the left of the illustrations are noted the ID of the referents along with their attributed gesture (see Tab. 3.1 and Tab. 3.2). Illustrations taken from <https://rb.gy/gxegrt>.

CONCLUSION

4.1 Achievements of this work

In this work, we present a systematic literature review and an elicitation study on the Myo armband developed by Thalmic Labs , we first presented the context around gesture recognition techniques, before focusing on the Myo armband. After explaining the functionality of this armband, which consists of 8 electromyographic sensors and an 8-axis inertial measurement unit, we conducted a systematic literature review to address the question, "what are the diverse applications of the Myo armband?" Based on 103 papers, we categorized the applications into four main domains: health science (22%), robotics (17%), lifestyle and recreation (29%), and computational research (33%). Despite being discontinued since 2018, the Myo armband remains a significant device in its field, continuing to attract research interest and practical applications. The next part of our work involved an elicitation study focused on the context of cycling. After interviewing 25 participants, we categorized the numerous gestures performed into five major classes, demonstrating the correlation between certain types of gestures and their associated commands. Additionally, we found that while the design of the Myo armband was appreciated, its practical application received mixed reviews.

Combining both studies reveals that very few applications have considered an elicitation process before conducting their investigations. This highlights the importance of understanding user needs and preferences prior to developing new applications. Therefore, anyone interested in creating a new application for the Myo armband can use this work as a dual source of valuable information: identifying where their appli-

cation idea fits within existing research, and following a user-centered methodology to ensure intuitive and effective user experiences.

4.2 Perspectives

Both parts of the work were conducted in parallel, which did not allow us to use the conclusions of the SRL in our elicitation work. Given the results obtained, several applications have come to mind. For example, based on what has been done with biometric recognition, we envision a more general application of the smartphone with the Myo armband. In situations where the smartphone's touchscreen is impractical to use, such as when it is damaged or in rainy conditions, the Myo armband could serve as an alternative interaction method. Basic commands, such as the camera application, emergency calls, and unlocking the smartphone, could be communicated via Bluetooth to our armband, for instance.

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Appendices

APPENDIX

ONE

DEMOGRAPHIC AND CONSENT FORMS

QUESTIONNAIRE POUR PARTICIPER A L'EXPERIENCE

Titre de l'étude: Elicitation de gestes
Professeur: Prof. Jean Vanderdonckt, UCLouvain
Expérimentateurs: Antoine Ghyoot, Arthur Golenvaux
Email de contact: jean.vanderdonckt@uclouvain.be

Données personnelles (qui seront anonymisées)

Code anonyme: (à attribuer par l'expérimentateur)
Prénom : (anonymisés dans la base de données)
Nom de famille :
Genre : ☐ Femme ☐ Homme
Age : (années)
Profession : ☐ Etudiant ☐ Cadre ☐ Employé
☐ Indépendant ☐ Pensionné ☐ Chômeur
☐ Autre : (préciser s.v.p.)
Domaine d'activité: (p. ex., administration, enseignement)
Etudes : (domaine de votre dernier diplôme)

J'utilise un ordinateur fréquemment:	Pas d'accord	1	2	3	4	5	6	7	D'accord
J'utilise un smartphone fréquemment:	Pas d'accord	1	2	3	4	5	6	7	D'accord
J'utilise une tablette fréquemment:	Pas d'accord	1	2	3	4	5	6	7	D'accord
J'utilise des objets connectés fréq. :	Pas d'accord	1	2	3	4	5	6	7	D'accord
Je fais du vélo fréquemment :	Pas d'accord	1	2	3	4	5	6	7	D'accord

Données expérimentales

Connaissez-vous l'appareil utilisé dans l'expérience ☐ Oui ☐ Non
Combien de fois l'utilisez-vous? Rarement 1 2 3 4 5 6 7 Fréquemment

CONSENTEMENT A PARTICIPER A UNE EXPERIENCE SCIENTIFIQUE

Titre de l'étude: Elicitation de gestes
Professeur: Prof. Jean Vanderdonckt, UCLouvain
Expérimentateurs: Antoine Ghyoot, Arthur Golenvaux
Email de contact: jean.vanderdonckt@uclouvain.be

Nous vous remercions de contribuer à la recherche scientifique en participant à cette expérience. L'expérimentateur vous expliquera le but de l'expérience et les questionnaires à remplir. Posez vos questions éventuelles à l'expérimentateur avant de débiter l'expérience. Vous pouvez obtenir une copie de ce formulaire de consentement et vous y référer à tout moment.

Par la présente, j'accepte de prendre part à l'expérience qui m'a été expliquée. Je peux l'arrêter à tout moment en notifiant l'expérimentateur sans conséquence. Une fois ce consentement signé, un identifiant anonyme sera assigné de sorte que mon nom et mon prénom n'apparaîtront nulle part ailleurs que sur ce formulaire. Je consens à ce que les données recueillies dans cette expérience soient traitées à des fins scientifiques, de manière strictement confidentielles et en accord avec la réglementation du respect de la vie privée de l'UCLouvain et du Règlement général de protection des données (RGPD). Toute photo ou vidéo enregistrée lors de l'expérience ne permettra pas d'identifier le participant, notamment en évitant la tête ou en la floutant.

- ☐ Veuillez cocher cette case si vous acceptez d'être éventuellement contacté ultérieurement pour d'autres expériences menées à l'UCLouvain ou pour une interview.
Le cas échéant, adresse e-mail:

Déclaration du Participant:

Je, soussigné, atteste que l'expérience susmentionnée m'a été expliquée, que je l'ai comprise, et que j'accepte d'y prendre part. J'ai lu les termes ci-dessus et les formulaires accompagnant et je comprends ce que l'expérience va analyser.

Signature:

Date:

Déclaration de l'Expérimentateur:

Je, soussigné, confirme avoir expliqué le but de l'expérience, sa procédure et ses questionnaires et, le cas échéant, les risques prévisibles de l'expérience proposée au participant.

Signature:

Date:

Identifiant assigné au participant :

APPENDIX

TWO

SLIDES OF THE ELICITATION STUDY



1

THE ELICITATION STUDY



❑ Purpose of the study :

- ➔ Asking end-users to elicit their own gestures for a set of predefined functions through referents and reach a consensus
- ➔ Application : Eyes-free handling of some smartphone functionalities while biking in sight of reducing accident risks

❑ The device : Thalmic Myo Armband



Figure taken from Tatarian et al.

Working principle :

1. Sensoring muscle contractions through 8 electrodes placed around the forearm ;
2. Obtaining electrical signal from the processed data obtained at step 1 ;
3. Classifying the obtained signals based on a pre-defined gestures database ;
4. Executing the command related to the gesture given as input.

2

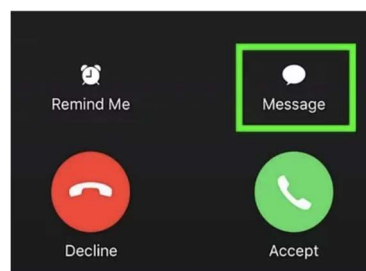
2

REFERENT ID – G3



Basic phone functionalities

Referent : Sending an predefined reply



3

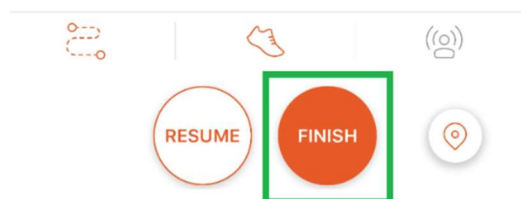
3

REFERENT ID – G6



Strava

Referent : Ending a route



4

4

REFERENT ID – G9



Strava

Referent : Making a lap

Lap	Distance	Elev	Time	Speed
1	1.54 km	-3 m	2:23	38.9 km/h
2	1.51 km	1 m	1:58	46.1 km/h



Lap	Distance	Elev	Time	Speed
1	1.54 km	-3 m	2:23	38.9 km/h
2	1.51 km	1 m	1:58	46.1 km/h
3	1.53 km	2 m	2:06	43.7 km/h

5

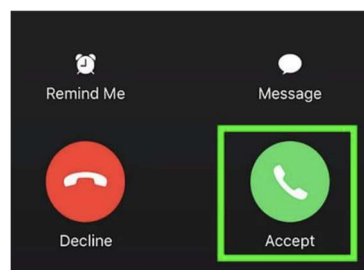
5

REFERENT ID – G1



Basic phone functionalities

Referent : Answering a call



6

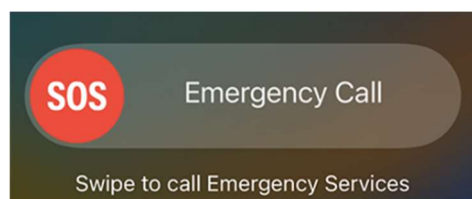
6

REFERENT ID – G4



Basic phone functionalities

Referent : Emergency call



7

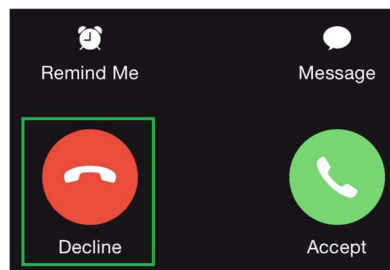
7

REFERENT ID – G2



Basic phone functionalities

Referent : Ending a call



8

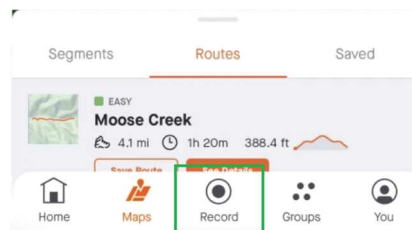
8

REFERENT ID – G5



Strava

Referent : Starting a route



9

9

REFERENT ID – G12



Bike functionalities

Referent : Turning on front and back lights



10

10

REFERENT ID – G8



Strava

Referent : Ending a chronometer

TIME

 00:00:04

||

11

REFERENT ID – G13



Bike functionalities

Referent : Turning off front and back lights



12

12

REFERENT ID – G7



Strava

**Referent : Start a
chronometer**

TIME

▶ 00:00:00

13

13

REFERENT ID – G10



Strava

**Referent : Turning on
performance status**

Lap	Distance	Elev	Time	Speed
1	1.54 km	-3 m	2:23	38.9 km/h
2	1.51 km	1 m	1:58	46.1 km/h
3	1.53 km	2 m	2:06	43.7 km/h
4	1.51 km	-1 m	2:07	42.9 km/h
5	1.51 km	-1 m	2:10	41.9 km/h
6	1.51 km	0 m	2:10	41.9 km/h

↓ $S1 < S2 \rightarrow$ Continuous vibration
↓ $S3 > S4 \rightarrow$ Pulsated vibrations

14

14

Strava

Referent : Turning off performance status

Lap	Distance	Elev	Time	Speed
1	1.54 km	-3 m	2:23	38.9 km/h
2	1.51 km	1 m	1:58	46.1 km/h
3	1.53 km	2 m	2:06	43.7 km/h
4	1.51 km	-1 m	2:07	42.9 km/h
5	1.51 km	-1 m	2:10	41.9 km/h
6	1.51 km	0 m	2:10	41.9 km/h

 $S1 < S2 \rightarrow$ Continuous vibration
No information
 $S3 > S4 \rightarrow$ Pulsated vibrations

SPREADSHEETS FOR THE SRL AND ELICITATION STUDIES

Disclaimer : all links will expire by the end of May 2025

We provide a link to access the spreadsheet used during the systematic literature review (SpreadsheetSRL, see below). On the first sheet, each row represents an article, with columns detailing various characteristics across different domains. For example, the initial columns provide information about the participants, while the later columns list types of gestures, with a 'Y' indicating if a gesture is included in the study. The columns sometimes use abbreviations, and their meanings are explained on the second sheet. The second sheet consists of explanations for each column's abbreviations, and it also contains formulas and tables that count occurrences in the 4 domains of applications, but also other analyzed features. Additionally, this sheet includes various charts used in this report. **Here is the link : SpreadsheetSRL.**

Finally, one can find the two spreadsheets used for the elicitation study. The first and main one (SpreadsheetESa) served at encoding the data from the study and to retrieve most of the figures presented in Chapter 3. It can be divided into two parts, each corresponding to the two first sheets. While the first sheet is dedicated to the data of the participants, the second gathered all the results from the study itself (i.e. Gestures' categorization, Goodness of Fit, Time of Thinking and Ease to Perform). The second spreadsheet (SpreadsheetESb) was dedicated to the post-processing of the gestures. It consists in fifteen tables, each related to a referent, where the descriptions, according to the same protocol, and categorization of the twenty-five participants' gestures are performed. **Here are the links : SpreadsheetESa and SpreadsheetESb.**

End-User Interaction by Electromyography - the case of the Thalmic Myo Armband

Resume

The past two decades have witnessed a rapid and worldwide rise in power of the smartphones' usage. From this expansion emerged a competition between the visual-based manner of interacting with mobile devices and the visual attention required from the users towards their environment - crucial in multiple mobile contexts (e.g. driving, running, cycling). Given that context, Thalmic Labs developed an electromyographic armband capable of controlling connected objects via gestures recognition. This device will be the central piece of this work, the latter's purpose being twofold. At first, an inventory of armband's applications will be draw up through a systematic review of the literature. Secondly and finally, a catalogue of gestures for a new application implemented in the scope of this work will be proposed. This catalog will be set up by means of an elicitation study.

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