UNIVERSITY OF NAPLES
"FEDERICO II"

SCHOOL OF MEDICINE AND SURGERY

Department of
Public Health and Predictive Medicine

PhD Thesis

"An EEG-based Method for Fall Risk Prevention in Daily Life: Theoretical Background, Applications, and Perspectives"

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2021 - 2022

Tutti i più grandi avvenimenti del mondo
hanno sempre luogo nel cervello

- Oscar Wilde -

Il progressivo sviluppo dell'uomo dipende dalle invenzioni.
Esse sono il risultato più importante delle facoltà creative del cervello umano.
Lo scopo ultimo di queste facoltà è il dominio completo della mente sul mondo materiale,
il conseguimento della possibilità di incanalare le forze della natura così da soddisfare le esigenze umane.

- Nikola Tesla -

Una vita senza ricerca non è degna di essere vissuta.

- Socrate -

A te che sei qui oggi....
e hai creduto in me fino alla fine...

Alla mia splendida grande Famiglia
Ai miei Amici
Alle persone che Amo...
quelle che mi sono vicino ogni giorno
e quelle che mi guardano da lontano☆!!!

Acknowledgments

Only in a printed version

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Abstract

In this thesis, an EEG-based method for the prevention of falls to be employed in daily-life application is proposed. According to The World Health Organization (WHO), falls are a worldwide problem. They represent the second cause of death from unintentional injuries, and produce significant costs in charge to the healthcare system. Recent studies have shown that gait is not a higher order automated process, but includes a much more elaborate cortical involvement. The gait requires the use of complex cognitive abilities such as: i) an adequate cognitive load related to an effective cognitive engagement; ii) the use of the Executive Functions (EFs) during walking; and above all iii) the ability to allocate attentional resources while performing multiple concurrent activities during the walk. In order to develop a fall prevention system to be used in daily-life applications, a wearable and high portable EEG device was identified. The functional analysis of the EEG *ab medica*® *Helmate* was performed to verify its employability in the research of the cerebral correlates during the gait. To monitor cognitive load, an EEG-based method for cognitive engagement detection was realized in the learning and rehabilitation contexts. To identify which EEG features are mostly used in the literature for the evaluation of the EFs and their subfunctions, a review was carried out. Finally, a study for the assessment of attention/distraction during a dual-task oddball protocol was performed.

Thus, the detection of attention, cognitive engagement, and EFs during dual-task walking allows to identify: i) a condition of impairment/overload of the subject's cognitive resources; and ii) the onset of a dangerous condition. Therefore, an EEG-based system and method for fall risk prevention can be implemented.

Keywords: fall prevention, gait, EEG, attention, executive functions, cognitive engagement

List of publications

Journal publications:

1. Andrea Apicella, Pasquale Arpaia, Mirco Frosolone, Nicola Moccaldi, *"High-wearable EEG-Based Distraction Detection in Motor Rehabilitation."*, **Scientific Reports**, 2020, 11(1), 1-9. Nature.com. doi:10.1038/s41598-021-84447-8

2. Pasquale Arpaia, Umberto Cesaro, Mirco Frosolone, Nicola Moccaldi, Maurizio Taglialatela. *"A micro-bioimpedance meter for monitoring insulin bioavailability in personalized diabetes therapy."* **Scientific Reports**, 2020, 10(1), 1-11. Nature.com. doi:10.1038/s41598-020-70376-5

3. Pasquale Arpaia, Federica Crauso, Mirco Frosolone, Massimo Mariconda, Simone Minucci, Nicola Moccaldi, *"A Personalized FEM Model for Reproducible Measurement of Anti-inflammatory Drugs in Transdermal Administration to Knee."*, accepted to **Scientific Reports**, 2021.

4. Andrea Apicella, Pasquale Arpaia, Mirco Frosolone, Giovanni Improta, Nicola Moccaldi, Andrea Pollastro, *"EEG-based Measurement System for Student Engagement Detection in Learning 4.0."*, under review to **Scientific Reports**, 2021.

5. Pasquale Arpaia, Fabio D'Asaro, Mirco Frosolone, Marco Grazioso, Giovanna Mastrati, Nicola Moccaldi, Luca Raggioli, Silvia Rossi, *"Data-fusion based adaptive rehabilitation system: a pilot study."*, to be submitted to **User Modeling and User-Adapted Interaction**, 2021.

6. Pasquale Arpaia, Loredana Cristaldi, Mirco Frosolone, Ludovia Gargiulo, Francesca Mancino, Nicola Moccaldi, *"EEG features of executive functions employed in the diagnosis and treatment of children with ADHD: a review."*, to be submitted to **Topics in cognitive science**, 2021, Wiley-Blackwell.

Conference proceedings:

1. Leopoldo Angrisani, Pasquale Arpaia, Francesco Donnarumma, Antonio Esposito, Mirco Frosolone, Giovanni Improta, Nicola Moccaldi, Angela Natalizio, Marco Parvis, *"Instrumentation for Motor Imagery-based Brain Computer Interfaces relying on dry electrodes: a functional analysis."*, **IEEE International Instrumentation and Measurement Technology Conference (I2MTC)**, May 2020, (pp. 1-6). IEEE. doi: 10.1109/I2MTC43012.2020.9129244

2. Andrea Apicella, Pasquale Arpaia, Mirco Frosolone, Giovanni Improta, Francesco Isgrò, Nicola Moccaldi, Angela Natalizio, *"EEG-based attention assessment in motor-rehabilitation."*, **24th IMEKO TC4 International Symposium and 22nd International Workshop on ADC and DAC Modelling and Testing**, 2020, pp. 17–22.

3. Giovanni Annuzzi, Pasquale Arpaia, Umberto Cesaro, Ornella Cuomo, Mirco Frosolone, Sabrina Grassini, Nicola Moccaldi, Isabella Sannino, *"A customized bioimpedance meter for monitoring insulin bioavailability."* **IEEE International Instrumentation and Measurement Technology Conference (I2MTC)**, May 2020, (pp. 1-5). IEEE

Introduction

In the Public Health the falls represent an important issue. According to the WHO, more than six thousand fatal falls occur each year, making the falls the second leading cause of death from unintentional injuries, after road accidents [1]. The rise in life expectancy leads to an increase in people's comorbidity and frailty. The physiological changes caused by aging are overlap the symptoms of chronic degenerative diseases exposing the subject to a greater risk of falling. According to the WHO, "The aging of the population is a triumph of humanity but also a challenge for society" [1]. The fall, in addition to creating an emergency situation within the Operating Unit or the Health Service, can also cause serious damage to the patient. The consequent injuries related to the falls involve high costs for Public Health: medical treatment, examinations and specialist visits become necessary, and the hospitalization times lengthen. The economic impact of falls is critical for the families, the community, and the society. In America, each year about 50 $ billion is spent on medical costs for non-fatal fall injuries, and 754 $ million is spent for fatal falls [2]. In 2007, WHO created a model for the prevention of falls based on three fundamental pillars:

1. the awareness of the importance of falls prevention;

2. the recognition and the assessment of fall risk factors;

3. the identification and implementation of realistic and effective interventions.

Thus, the aim of the WHO is to implement strategies and introduce new systems to reducing the probability of falling.

The phenomena underlying the cause of the loss of balance, of incorrect gaits and therefore of falls are: i) the alterations in cortical activation linked to aging, ii) the lower cortico-muscular coherence, iii) the greater allocation of cognitive resources related to the cognitive engagement, iv) the impairment in EFs, and v) the allocation of attention to multiple simultaneous tasks. Until recently, gait has been considered as a largely automated motor act requiring only minimal higher-level cognitive input. The postural regulation has been assumed to be under the control of the subcortical structures of the brain and spinal cord. Recent studies identify a much more complex cortical involvement in the postural response [3].

From a physiological point of view, the postural control of gait has been extensively studied. The muscle activity is controlled by the Central Nervous System (CNS) which acts by integrating the different musculoskeletal, visual, and vestibular inputs [4]. The role of the CNS and the subcortical structures for the adaptive feedforward and feedback adjustments in order to reduce the risk of loss of balance is well documented [5, 6, 7]. However, although the amount of information received by the brain is well known, the causes of falls and how to reduce their occurrence are still under discussion. An impaired gait adaptability (i.e., a reduced ability to change walking speed or direction as required) reduces the ability to avoid obstacles and increases the risk of falling. This situation becomes more critical in patients suffering from specific diseases (e.g., post-ictus, Parkinson, idio-pathic fallers, Alzheimer, brain injuries etc.) [8, 9, 10].

In this direction, it is necessary to identify: the mechanisms occurring in the brain during gait, and the external inputs affecting cerebral correct functioning. In gait evaluation, recent studies indicate the importance of complex brain processes such as: the profuse cognitive engagement, the employed EFs, and in particular the attention towards concurrent tasks [11]. These cognitive processes appear to work together during walk. Therefore, through their analysis, the systems capable to reduce the occurrence of falling, can be identified.

If the gait was an automated system of superior cortical order, walking would not require attention. Therefore, performing a simultaneous task during walk should not affect the gait or the other activity. Referring to this issue, many researchers starting work on gait assessment during a dual-task [12, 13, 14]. The neurological theories underlying the dual-task are based on one assumption: people have a limited capacity for processing information if they invest all them cognitive resources to perform a given task [15]. When a second task is introduced, these resources are no longer sufficient to meet the new demand and there is a decline in performance in one or both tasks. In particular, the dual-tasks deplete the cognitive resources in terms of attention, EFs and cognitive engagement [16]. The identification of these neural processes during a dual-task can: i) confirm the neurological hypotheses of previous studies, and ii) be an important first alarm for a dangerous situation.

Numerous studies are investigating the neural correlates underlying the phenomena related to the gait, the balance, and the posture during walking

[17, 18]. For this purpose, the most employed techniques are neuroimaging (fMRI, PET, etc.) and electroencephalography (EEG). However, the imaging techniques are very limited due to the time delays associated with the hemodynamic response, and to the expense and limited mobility of the equipment [19, 20]. The EEG is far less restrictive than the other imaging techniques. The consumer-grade EEG caps promote the accessibility of the neural signal measurement with reduced costs and simpler configuration protocols. In this thesis, all the aforementioned aspects related to the cerebral processes of gait, are analyzed. In particular:

- *Chapter 1*: **Falls Prevention in Healthcare System**. Firstly, a contextualization about the risk of falling and the importance of prevention is provided. Secondly, the neural gait correlates and the EEG features used in literature for gait evaluation are evidenced, in the background.

- *Chapter 2*: **Functional Analysis of the EEG System**. Two EEG systems for walk analysis are highlighted: the *emotiv epoc+*, and the *ab medica*® *Helmate*. Than, the employability of the new EEG system *Helmate* in the gait is demonstrated. A functional analysis study was carried out to highlight the advantages of using this system for detecting EEG neural correlates related to gait.

- *Chapter 3*: **Cognitive Engagement in Learning and Rehabilitation**. The EEG-based detection of cognitive engagement in learning and rehabilitation contexts was carried out as starting point for fall prevention applications.

- *Chapter 4*: **EEG Features for Executive Function Identification**. A systematic review on EFs was realized with the purpose of identifying the main EEG features employed for EFs detection. The found EEG features can be exploited to evaluate some of the EFs more involved during the walk, and supervise their overload.

- *Chapter 5*: **Attention Detection during Dual-task Execution**. An EEG-based method for motor rehabilitation is proposed to detect the attention/distraction condition during an oddball paradigm. The assessment of the attention condition during dual-task walking is fundamental to prevent the risk of fall.

Chapter 1

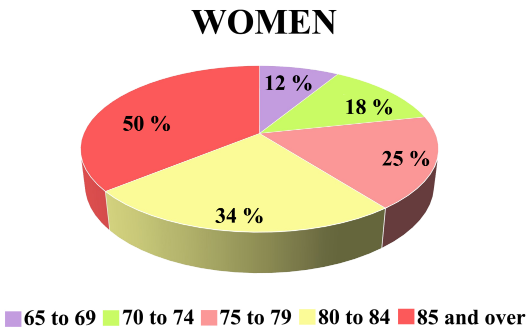
Falls Prevention in Healthcare System

1.1 Rationale

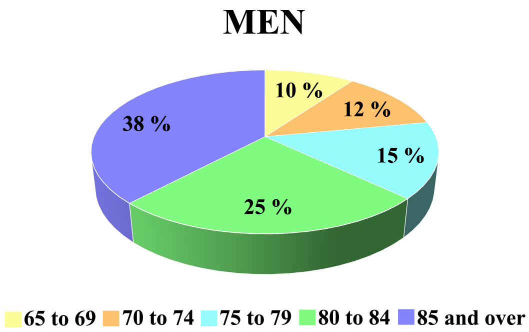
The fall is defined as an event producing a sudden and involuntary change in posture that leads the subject to hit the ground or an inferior element with any part of the body [1]. The problem of falls plays a fundamental role within the health context. The International Classification of Diseases reserves 19 codes to identify problems related to falls (ICD-9 codifies the falls related diseases from E880 to E888, the ICD-10 from W00 to W19). In the Public Health falls represent an important issue. According to the WHO, more than six thousand fatal falls occur each year, making the falls the second leading cause of death from unintentional injuries, after road accidents [1]. About 28-35 % of people (aged 65 and over) fall each year [21, 22, 23] Fig. 1.1. This percentage rises to 32-42 % in the over 70s [24, 25, 26].

The falls are the consequence of a complex interaction of risk factors affecting the type and severity of the injury. The studies show that main risk factors are: i) biological factors (age, sex, and especially changes related to aging, such as the decline in physical, cognitive and emotional abilities, and comorbidities associated with chronic diseases); ii) behavioral factor (taking multiple medications, excess alcohol and a sedentary lifestyle); iii) environmental factors of interaction with external elements (narrow steps, slippery surfaces, loose carpets and insufficient lighting); and iv) socio-economic factors (low income, low level of education, inadequate housing, lack of social interaction, limited access to social health services - especially in the most isolated areas) Fig. 1.2.

The elderly people living in nursing homes fall more frequently than those



(a) risk of falling by age for *women*



(b) risk of falling by age for *men*

Figure 1.1: Age and sex based percentage of the risk of falling: a) women and b) men.

living in communities. About 30-50 % of hospitalized in long-term care falls each year and 40 % of these are victims of recurrent falls [26]. The hospitalization rates due to falls, in 60s and over, reach even 8.9 per thousand people in industrialized countries. The falls lead to a 20-30 % of medium-serious accidents and are the underlying cause of 10-15 % of all access to the emergency room and more than 50 % of hospitalizations for injury [27]. The main causes of hospitalization for fall accidents are the fracture of the femur, head trauma and damage to the upper limbs. The increase in life expectancy leads to a situation of comorbidity and fragility of the people.

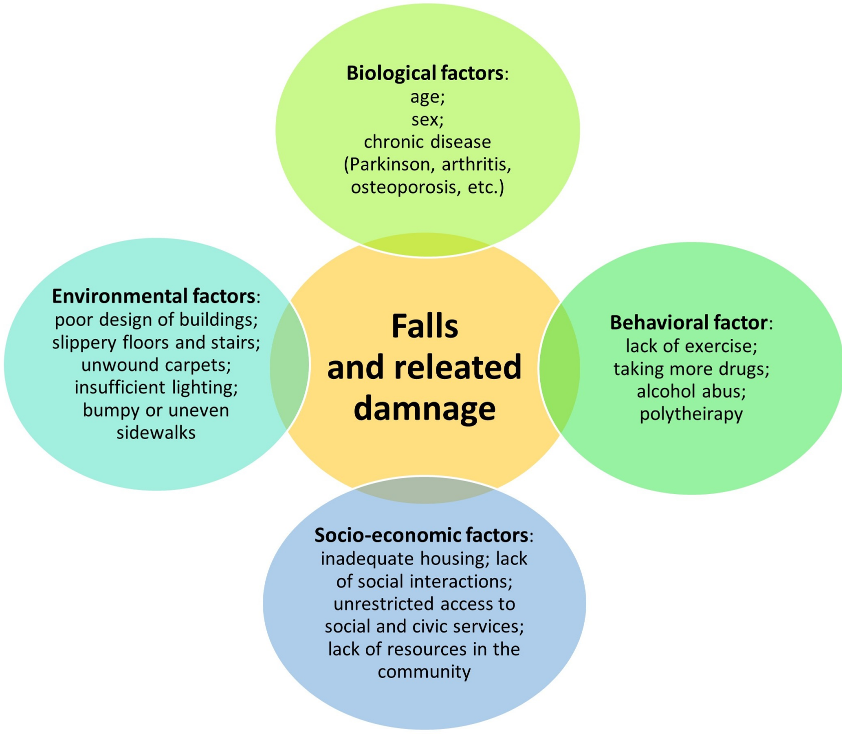


Figure 1.2: Risk risk factors and their interactions with falls and resulting injuries.

The physiological changes caused by ageing, overlap the signs and symptoms of chronic degenerative diseases that expose the subjects most to risk of falling. The falls and consequential accidents result in high costs for public health due to the medical care required. As a result of the hospitalization of patients, especially the elderly, the physical consequences (trauma and fractures) compromise the quality of life and increase the risk of premature death. The consequent injuries related to the falls involve also high costs for Public Health: medical treatment, examinations and specialist visits become necessary, and the hospitalization times lengthen. The economic impact of falls is critical for the families, the community, and the society. The costs caused by falls are organized according to two aspects:

- direct costs: include health costs incurred for drugs and adequate services, for example medical visits for treatment and rehabilitation (also involving various degrees of exposure to ionizing radiation with a consequent increase in the probability of damage);

- indirect costs: these are company losses due to patients or family members not being present at work.

In the hospital environment, the falls are positioned in fourth place among the causes for damages in the hospital: one out of ten are accidental falls and lead compensation claims for 4.2 million euros per year. In the 97 % of cases, accidental falls resulted in injuries, but in 2.4 % of cases they resulted in death. In America, each year about 50 $ billion is spent on medical costs for non-fatal fall injuries and 754 $ million is spent for fatal falls [2]. Among the factors that influence the risk of falls, age is certainly one of the most important, especially in relation to the increase in the life expectancy of people.

According to the WHO, "The aging of the population is a triumph of humanity but also a challenge for society" [1]. The number of over 60s is increasing faster than that of any other age group. This number is estimated to be at least two billion by 2050. For this reason, fall prevention is an important challenge for the global population. In 2007, WHO created a model for the prevention of falls based on three fundamental pillars:

1. the awareness of the importance of falls prevention: all sectors of society need to contribute to raising awareness of the problem of fall prevention;

2. the recognition and the assessment of fall risk factors: is necessary to improve the assessment and the identification of the critical factors favoring the risk of falls;

3. the identification and implementation of realistic and effective interventions: numerous studies have shown that interventions can be effective in reducing falls in the elderly, so it is necessary to search for new systems and technologies for the prevention of falls [28].

In this context, for example, the OU Risk Management since 2009 has activated a surveillance system on patient falls, through the use of a specially developed "fall detection cards". After the first six months of the survey, the "Project for the prevention of accidental falls of patients-users and visitors in the Asl Rm6 structures" was developed. The project was implemented through information and training meetings with the health personnel of the Asl Rm6. In line with the Ministerial Recommendation n.13 of November 2013 (*Recommendation for the prevention and management of patient falls in health facilities*), all the UU.OO and the Hospital and Territorial Services compile and send the "fall report form" to the Risk Management secretariat. However, this example is limited to a reporting analysis. New strategies must be implemented and new systems introduced to reduce the probability of falling. This thesis focuses on these aims.

1.2 Background

The phenomena underlying the cause of the loss of balance, of incorrect gait and therefore of falls are: (i) the alterations in cortical activation linked to aging, (ii) the lower cortico-muscular coherence, (iii) the greater allocation of cognitive resources related to the cognitive engagement, (iv) the impairment in Executive Functions (EFs), and (v) the allocation of attention to multiple simultaneous tasks. Gait, balance, and posture are inextricably linked because one depends on the others and vice versa. Not only muscle aging is responsible for people tumbling. Another possible cause is the slowing down of reflexes making the movement more tiring and complex. Poor posture and a bad gait can contribute to make the reflexes slow or ineffective, or even get an already critical situation worse. Until recently, gait has been considered as a largely automated motor act requiring only minimal higher-level cognitive input. The postural regulation has been assumed to be under the control of the subcortical structures of the brain and spinal cord. Different studies identify a much more complex cortical involvement in the postural response [3]. Recent studies have shown how the vertical posture is the product of a complex dynamic cognitive system based on the integration of inputs received from multimodal sources, analyzed at a deep cortical level. Mergner and Matari, documented through EEG and fMRI analyzes, the possible existence of neural detectors which intervene when postural instability is correctly identified [29, 30]. Some studies found an interaction between postural control and cognitive task performance, indicating that postural control is not a fully automatic process but requires active cognitive processes [16]; complex information processing [31]; and the perception, the decision making and the motor control [32, 33]. The current theories transcend previous beliefs based on minimum input and consider gait as a complex system influenced by several factors. Indeed, gait involves multiple areas such as neurology, physiology, biomechanics, as well as physics and neuropsychology. From a physiological point of view, the postural control of gait has been extensively studied. Muscle activity is controlled by the Central Nervous System (CNS) which acts by integrating the different musculoskeletal, visual and vestibular inputs [4]. The role of the CNS and the subcortical structures for the adaptive feedforward and feedback adjustments, in order to reduce the risk of loss of balance, is well documented [5, 6, 7]. However, although the amount of information received by the brain is well known, the causes of falls and how to reduce their occurrence are still under discussion. An impaired gait adaptability (i.e., a reduced ability to change walking speed or direction as required) reduces the ability to avoid obstacles and increases the risk of falling. This situation becomes more critical in old patients and patients suffering from specific diseases (e.g., patients with strokes, Parkinson, Ictus, etc.) [8, 9, 10]. The aging process is associated with a neurophysiological degeneration and multisensory inhibition and involves: i) the loss of motor neurons, ii) the decreased nerve conduction, iii) the limited proprioception, iv) the muscle weakness, and v) the impaired cognitive processing [34]. According to Horak [35], older individuals lack the ability to quickly re-weigh sensory information and adapt to environmental changes due to a decline in cognitive processing skills. The lack of ability to adapt efficiently and effectively to environmental changes can be a contributing factor to gait instability. In walk analysis, recent studies indicate the importance of complex brain processes such as: the profuse cognitive engagement, the employed EFs, and in particular the attention towards concurrent tasks [11]. These cognitive processes appear to work together during walk. Therefore, through their analysis, systems capable to reduce the occurrence of falling, can be identified. The term Executive Function refers to a series of top-down higher-order cognitive processes which elaborate information coming from different sensory systems. The EFs are necessary when people have to concentrate and pay attention [36]. Generally, EFs are divided into three main components: working memory, inhibition (i.e., behavioral inhibition, selective attention and cognitive inhibition), and cognitive flexibility. Starting from to these main components, EFs of a higher order such as reasoning, problem solving, and planning [37, 38] are derived. According to Lezak [39], six high-order EFs exist and intervene directly within the walk:

a) the *Volition* is the capacity for intentional behavior, for formulation of a goal or intention, and for initiation of activity. Its impairment can cause loss of mobility due to reduced motivation or the decrease in the inner urge to move;

b) the *Self-awareness* is the ability to place psychologically and physically in the physical environment and the ongoing. Its impairment can cause an incorrect estimate of physical limits, can lead to an inadequate assessment of environmental risks and increase the risk of falling;

c) the *Planning* is the identification and organization of the steps and elements needed to carry out an intention, influencing also on the ability to conceptualize changes from present circumstances, conceiving alternatives, weighing, and making choices, controlling impulses and using memory. Its impairment can cause deficits in decision-making skills while walking; inefficient, defective or even risky choices; loss of road or time, or increased effort to get to the desired destination;

d) the *Response inhibition* allows to ignore irrelevant sensory inputs, overcome primary reflexes, and filter out distractions to solve problems. Its correct functioning is essential during walking in complex everyday environments, and allows to focus on the walking;

e) the *Response monitoring* enables one to compare ongoing actions with an internal plan and to detect errors. This component is important to walk in complex environments and making correct choices.

f) the *Attention* during dual-task is the ability to adequately allocate attentional resources when several concurrent activities are carried out at the same time.

Therefore, impaired EFs can cause alterations in cognitive processes, preventing the correct gait functioning of the walk, the gait, and the posture movements and promoting the risk of falls. From an anatomical and physiological point of view, many studies deal with the mapping of the brain in order to identify the areas most involved in the processes related to the EFs. Although in principle many studies identified the frontal and prefrontal areas as the main areas involved in the cognitive processes related to EFs, Stuss and Alexander refuted this hypothesis [40]. Some meta-analysis studies based on three classic tests for EFs (stroop test, Wisconsin test and verbal fluency test) showed that the performance of the test subjects was sensitive above all to damages of the frontal lobe (results confirmed with poor performance in the test) [41]. Today, the authors suggest that even if the frontal lobes participate to a greater extent, the EFs involve different areas of the brain. Therefore, a study allowing a simultaneous analysis of multiple brain areas is needed in order to obtain complete and adequate information on the phenomenon. As mentioned above, epidemiological studies show that age certainly appears among the risk factors for falls. This is also confirmed on a physiological level. Some studies indicate that even healthy elderly people have on average a reduction in some components of EFs. Attention, abstract thinking, mental flexibility tend to decrease with age. However, it is only through the use of specific tests that it is possible to identify the degree of this impairment. Impairment of the EFs does not represent the only cause of falls in the elderly (the WHO indicated in addition to the biological risk factor, the behavioral and economic ones). In the "InChianti" study carried out on 900 non-demented elderly adult patients with an average age of 74.6 $\pm$ 6.7 years, the walk at different speeds and on obstacle courses, was assessed. The subjects filled in tests for EFs evaluation and were divided into groups according to the achieved scores. The groups were asked to walk at a moderate pace in both obstacle-free and obstacle walking conditions.

The delta band power was then evaluated in the two different conditions. The results clearly show that:

- The average speeds in obstacle-free walking conditions are the same for the three symptom groups (in single task) and walking conditions do not vary with EFs;
- during walking with obstacles, the speeds are significantly different in the three groups and the different impairment level causes a change in gait.

Other studies investigated the relationship between EFs, walking speeds and stride times. Thus, the link between gait and EFs in a single task was confirmed, even though the correlation dynamics are still to be explored. On the other hand, studies using only one specific EF during walking conditions were mostly evaluated. Among the studied EFs, attention is the most widely investigated. The term finds its theoretical roots in many previous theories, from Functionalist, Behaviorist theories, to Gestalt theories up to the most recent definition of Ladavas and Berti. These latter established: "If it is possible to define the cognitive activity of the human being as the processing by the latter of information coming from the external environment, then Attention can be described: as that primary function that regulates this cognitive activity and that, through the filter and organization of the information received, allows the subject to issue adequate responses" [42]. Today, EFs researchers insert aspects of attention within the concept of EF. The term is linked to different processes related to how an organism becomes receptive to stimuli, and how it begins to process incoming and outgoing information [39]. However, there is no clear and comprehensive definition of the concept of attention. Posner and Petersen classified attention as a set of separate functions: selective or focused, sustained, distributed and alternated [43]. The focused or selective attention refers to the ability to filter information and stimuli, to the suppression of distractors and is often called concentration; the sustained attention refers to the ability to maintain concentration on a certain task for an extended period of time; the distributed attention to the ability to perform multiple tasks simultaneously; and the alternated attention to the ability of shifting attention from one task to another [44]. Therefore, according to Posner and Petersen, all the attentional functions are recruited during the different phases of the gait. For example, during walk: the divided attention plays an important role in multitasking and changing conditions; the focused attention allows to be receptive in sudden dangerous conditions; the sustained attention intervenes to complete the path correctly; and the alternated attention is essential to perform concurrent tasks. These concepts reflect the relationships between EFs and gait. Problem solving, inhibition, planning, visual-spatial working memory and reasoning, can be compared to the attentional functions indicated by Posner and Petersen.

If the gait was an automated system of superior cortical order, walking would not require attention. Therefore, performing a simultaneous task during walking should not affect the gait (or the other activity). Referring to this issue, many researchers started working on gait assessment during a dual-task [12, 13, 14]. The neurological theories underlying the dual-task are based on one assumption: people have a limited capacity for processing information if they invest all the cognitive resources to perform a given task [15]. When a second task is introduced, these resources are no longer sufficient to meet the new demand and there is a decline in performance in one or both tasks. Regarding these resources, there are three main theories: i) the models and the theories of *capacity sharing*, ii) *the bottleneck* (task-switching), iii) and those of *cross-talk* [45]. According to the theories of capacities each subject is able to share the attention skills between multiple tasks [46]. The people apparently perform several activities at the same time until one or more of these become too difficult. When this happens, more effort is required and therefore performance on one or both tasks can be degraded. Neurologically, people appear to have control over the distribution of the limited available resources across tasks; they may, for example, choose to allocate more skills to a task even though both are largely automatic. In this sense, the presence of an additional task during walking alters its execution (both the speed and the amplitude of the stride reduce) or the execution of the second competing task. The bottleneck theory argues that only a single activity can be correctly processed at a time [47]. For this reason, the second activity will be delayed until the resource is freed from the first one. According to some researchers, the delay occurs in the task response selection phase, while for others it can occur at any stage. Therefore, according to this theory, carrying out a concurrent task while walking must necessarily lead to either a slowed pace or a delay in the execution of the second task (detectable through a performance analysis). Finally, the multiple resource theory assumes that the execution of different tasks may require a certain number of resources [48]. When tasks require the same type of neurological resources, there is a deterioration in performance in the execution of tasks. Even in this case, therefore, walking while performing a concurrent cognitive task causes a deterioration in the performance of both or at least one of the two tasks. In relation to the exposed theories, many studies compared the performance of a walking task with and without the execution of concurrent cognitive tasks. A dual-task paradigm involves the subject performing two tasks requiring attention, competing for their cognitive resources [11]. An increase in the load of cognitive activity shows changes in the gait, such as slowing down, or a compensatory action. The greater the cognitive load that the subject experiences when performing a dual-task paradigm while walking, the more the subject is at risk of falling [49]. The therm "dual tasking" means the simultaneous execution of an active movement (motor skills) and a mental task (cognition), e.g. walking and talking at the same time, or go up the stairs and recognize the house key in a bunch of keys [16]. Many elderly people find difficult to manage daily dual tasking situations, because of the decrease of the cognitive reserves with age. For healthy young adults a process of reducing attention to a task or competitor can occur. The ringing of the telephone, the meow of the cat or the overflow of milk are able to capture all the attention resources available, therefore lacking for the performance of other contemporary signals, stimuli, and activities. It was shown that the likelihood of falling during a dual-tasking situation in the event of an abnormal gait is five times greater [50]. A pioneering study from 1997 gave a surprising result: the majority of subjects who stopped to answer the one question during walking task, suffered a fall within six months [51]. Many studies were carried out on healthy young adults and adults, healthy elderly people, and on patients with pathologies in dual-task conditions to evaluate the effects on gait. The analyzes performed on healthy young people and adults showed a slowdown in gait in conjunction with a double task [52]. In studies on healthy elderly people, the reduction in speed or a decrease in response times to the dual secondary task became more pronounced, probably due to the fact that in the elderly there was a reduction in cognitive engagement, EFs and attention due to aging [53, 54, 55]. The phenomenon is even more evident in patients with pathology (post-stroke, Parkinson, idiopathic fallers, Alzheimer, and brain injuries). Most of these patients have well-known deficits of EFs and attention. Patients with Parkinson's have impaired gait and loss of automatism of the feet, linked to cognitive deficits in working-memory, EFs and attention. When these patients were exposed to a double task, the attentional resources were all directed towards the cognitive task, causing an increase in gait anomalies [56]. The patients affected by idiopathic fallers, post stroke, Alzheimer disease, attention deficit hyperactivity disorder, and brain injuries, presented the same reduction in walking activity in relation to poor performance in the execution of the concurrent task [57, 58, 52]. The attentional and cognitive deficits affect mobility and task performance. The simple task of maintaining a posture alone requires greater attention due to the decrease in sensory information caused by the stroke or by the hyperactivity pathology [59, 60, 52, 61]. These results would confirm the hypotesis that the dual task increases the risk of falling among healthy elderly people with pathology, because it reduces the ability to allocate contemporary resources in terms of attention, cognitive engagement, and EFs [62, 63, 64]. From a physiological point of view, a double task challenges brain priorities. According to Bloem et al [65], healthy subjects during a dual task before keep the posture and then reduce the step to stabilize the gait, and maintain performance on the competing cognitive task. This does not happen in sick people. In this case, the subjects can not properly reduce the pace and stabilize the gait but the double task creates an imbalance in the use of attention, cognitive engagement, and EFs leading more easily the risk of falling [66]. The neural response to dual-task walking conditions may show a deficit not visible under single-task. The analysis of brain signals combined with the performances of the dual-task can therefore be a sensitive predictor for the risk of falls. For these reasons, the use of the dual-task in walking, balance and posture measures is widespread in the literature. There are many neuropsychological tests to solicit different EFs and attention: odball test, stroop test, verbal fluency, go-no-go test, tower of London, wisconsin card sorting test, bell test, etc. According to Galit, the task must be difficult enough to load the attention system, but not such as to cause stress or anxiety [16]. Many studies exploit the visual or auditory version of an oddball test as cognitive part in the dual-task during walking. [67, 68, 69]. The different above mentioned studies are all aimed at identifying how in the presence of a dual task the performance in the test or gait parameters are reduced or altered. The purpose of the present thesis is to confirm this hypothesis and to identify a method able to correctly discriminate between the conditions of simple walk and walk during a dual-task. The quick identification of a dual-task situation causing reduction of cognitive resources in terms of attention, EFs and cognitive engagement, can: i) confirm the neurological hypotheses of previous studies, and ii) be an important first alarm for a dangerous situation.

Numerous studies are investigating the neural correlates underlying the phenomena related to the gait, the balance, and the posture during walking [17, 18]. For this purpose, the most employed techniques are neuroimaging (fMRI, PET, etc.) and electroencephalography (EEG). However, imaging techniques have important limitations such as the time delays associated with the hemodynamic response, and the expensive and limited mobility of the equipment [19, 20]. The EEG is far less restrictive than the other imaging techniques. Consumer-grade EEG caps promote the accessibility of the neural signal measurement with reduced costs and simpler configuration protocols. The high temporal resolution of the EEG allows immediate neurological reactions to stimuli to be recorded. In a recent years, many studies exploited the EEG as a system for assessing the neurocognitive conditions underlying the problems of balance and posture in walking conditions. Rubega et al. acquired the EEG and EMG signals in healthy adults and young people in conditions of static and dynamic equilibrium in presence of dual-oddball-task. Main results were: a difference in the distribution of the EGG signal during the execution of the task between adults and young people; and a different distribution of the signal during the the oddball concurrent paradigm [70]. The final aim of these studies was to verify the presence of neural patterns during walk. Therefore, some important information on the neurological conditions at the base of the gait can be obtained by processing the features from the EEG signal. Based on existing literature, oscillatory frequency of the EEG signal can provide insight into the functional networks of the cortex as a defined range of frequencies are correlated with specific brain activities. Five distinct frequency bands have been identified in the human brain: δ, θ, α, β, γ, and μ. Studies carried out on the analysis of the EEG signal during walk identified that multiple bands are involved in balance and gait. Sloboun ov et al. [71] found a burst of gamma activity (especially in the frontal area) when a specific neural detector is activated to avoid falling. The γ waves are associated with attention; increased focus-attention provides for a high range power. Therefore, an increase in γ activity before the fall should lead to a recovery of equilibrium. The results of the study hypothesized there is an important role of the upper cortices in regulating balance during walking. Sipp et al., instead, [72] carried out an analysis on 26 healthy young subjects walking on a treadmill and on a beam. The results showed an increase in power in the θ band in multiple cortical areas, including the sensorimotor, anterior cingulate, and anterior parietal regions during beam walking. For the researchers, the increase in θ band power in the anterior cingulate cortex may be related to its role in error detection [73]. In this way, the neural system acts by identifying the error in the incorrect detection of equilibrium and responds with an increase in power in the θ band. In this study, as in the previous one, in-depth information is provided on the dynamism of human cortical brain substrates in gait and balance. The results suggest the existence of a multifocal cortical network involved in detecting and correcting loss of balance during walk. Khorev et al. [74] conducted an experiment consisting of maintaining gait on a platform. The results showed a decrease in the power in the α and β band when the subject maintains the condition of equilibrium. This is a further evidence of the possibility to detect complex neural signals underlining balance and gait through EEG analysis. Finally, Wagner et. Al, [75] recorded the EEG signal of 18 participants during walking on a treadmill in sync with an auditory signal. The speed of the walk was marked by the rhythm of the auditory signal used. Based on previous studies on brain activity, the researchers identified two distinct bandwidth oscillatory cortical networks. These networks intervene

Table 1.1: EEG systems, number and type of electrodes for the aforementioned articles.

Article	Employed EEG system	#channels	Type
[71]	Quick-Cap Electrode Helmet	25	gel
[72]	Active II, BioSemi	256	gel
[74]	Medicom MTD company	32	gel
[75]	g.tec combined amplifiers + modify EasyCap	108	dry

in adapting to the changes dictated by the auditory stimulation during gait. The μ rhythm [8-13] Hz and the power of the *low* β band [13–35] Hz decrease in the central and parietal cortex, while the power of the *high* β band [14-20] Hz increases in the frontal brain areas. According to researchers, two distinct patterns of band activity modulation lead gait adaptations: one likely serving for initiation and execution of movement; and the other, for the motor control and the inhibition. In the mentioned studies, EEG systems with a very large number of electrodes were employed. For the above presented works, a summary of the EEG systems, the number and the type of electrodes exploited, is showed in Table 1.1.

The described results offer various important opportunities of employing the EEG signal in the analysis of the posture, the gait, and the balance during walk. The EEG signal can be used for identifying the neurophysiological underpinnings of gait and give important information for the fall prevention. For the purposes of this thesis an easily wearable and daily-use system is strictly required. The previous studies identified in the frequency analysis (and in particular in the power spectral density) of the EEG signal, important features to obtain information on the recovery of equilibrium and, therefore, on the risk of falling. It was also highlighted the possibility to evaluate the gait and the risk of falling with dual-task experiments since the dual-tasks deplete the cognitive resources in terms of attention, EFs and cognitive engagement [16]. The analysis of the cognitive phenomena underlying this depletion, and the identification of specific EEG signal processing methods to detect each of these cognitive resources, is the aim of this thesis.

Chapter 2

Functional Analysis of the EEG System

2.1 Overview

The commercialized EEG systems offer a more financially accessible and *"easier to use"* option for obtaining EEG signals than the more complex systems used in medical research laboratories [76].

In order to propose a truthfully daily-use system, an analysis of the different systems on the market is carried out. Considering the technical specifications and costs, two possible alternatives were identified: *Emotiv Epoc+* and *ab medica® Helmate*. The Emotiv Epoc+, produced by Emotiv Inc., is a wireless headset measuring EEG signals at 14 different semi-wet electrode in the sites: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF42, using the Common Mode Sense (CMS) active electrode and the Driven Right Leg (DRL) passive electrode as references in P3 and P4 (Fig. 2.1). In addition, the neuroheadset incorporates: a signal amplifier, a C-R high-pass filter at 0.16 Hz, an analog low-pass filter at 85 Hz, a notch filter at 50 Hz to neutralize the high frequency noise, and a simple Analog to Digital Converter (ADC) to enable a sequential sampling at 128 Sa/s [78]. Although suitability of the Emotiv Epoc+ is dependent on the research paradigm, many evaluations have found the Emotiv Epoc+ performance to be satisfactory for non-clinical applications [76]. Others technical specifications of the *Emotiv Epoc+* are reported in [79].

The *Helmate*, on the other hand, is a new system being validated by the *ab medica®* company. The system consists of 8 dry channels placed in positions: Fp1, Fp2, Fz, Cz, C3 (or C5), C4 (or C6), O1, O2 (Fig.2.2).

Figure 2.1: EEG data acquisition system *Emotiv Epoc+* [77]

Figure 2.2: EEG data acquisition system *Helmate* [80]

The ten dry electrodes guarantees eight acquisition channels. The EEG signal is acquired by dry electrodes made of conductive rubber with an Ag/AgCl coating at their endings [81]. Three different types of electrodes, with different shapes, are used to pass hair and reach the scalp or join to the hairless areas (Fig. 2.3).

Figure 2.3: Different type of *Helmate* dry electrodes [80]

The output signal is recorded as difference between each of 8 channels and the ground electrode (Fpz) [82]. Then, the difference is referenced with respect to the electrode (AFz). A dedicated software (Helmate Software Manager) allows to check the contact impedance between the electrodes and the scalp. EEG signal is acquired with a sampling rate of 512 Sa/s. The acquisition software allows to use several filters (e.g., notch and IIR). This data acquisition system is a certified EEG system Class IIA (according to Medical Device Regulation (EU) 2017/745) with accurate components. A Texas Instruments analog front-end, the ADS129832 with a 24-bit, analog-to-digital converter (ADCs) with built-in programmable gain amplifiers (PGAs), internal reference, and an onboard oscillator, are exploited.

The device exhibits the following main metrological performances:

(i) CMRR: -115 dB;

(ii) eight low-noise PGAs and eight high-resolution ADCs (ADS1298, ADS1298R);

(iii) input-referred noise: 4 μVPP (150 Hz BW, G = 6);

(iv) input bias current: 200 pA;

and joined to the following operating performances:

(i) low power: 0.75 mW / channel;

(ii) data rate: 250 Sa/s to 32 kSa/s.

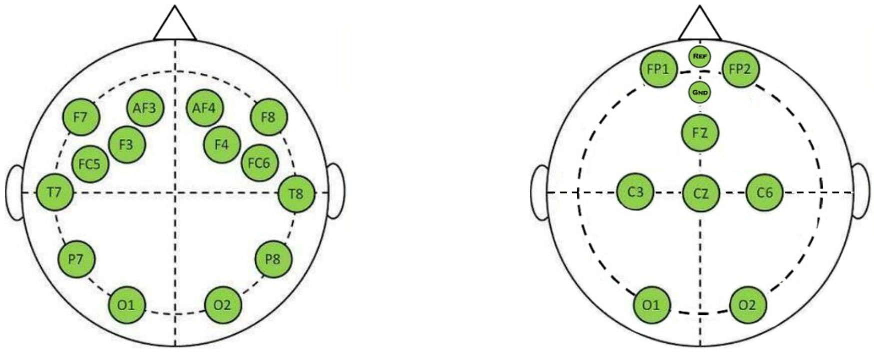
The major differences between the two systems emotiv epoc+ a) and Helmate b), are reported in the Table 2.1.

A comparison between the positioning of the two systems is shown in Fig.2.4.

Compared to the most employed and commercialized emotiv epoc+, the Helmet has a reduced number of electrodes, greater durability and good metrological performance. The Helmate is a new device, therefore, a first

Table 2.1: EEG Helmate and Emotiv epoc+ differences.

EEG system	*Helmate*	*Emotiv epoc+*
Number and type of electrodes	8 electrodes Dry	14 electrodes Semi-Wet
Electrodes positioning	Fp1, Fp2, Fz, Cz, C5/C3, C6/C4, O1, O2 AFz Ground Fpz Bias	Af3, F7, F3, Fc5, T7, P7, O1, O2, P8, T8, Fc6, F4, F8, Af4 Reference P3/P4
Fc [Sa/s]	512	256 or 128



(a) Emotiv epoc+ electrodes position **(b)** Helmate electrodes position

Figure 2.4: A comparison between the positions of the EEG system are evidenced in green: a) electrodes position of Emotiv epoch+, and b) the electrodes position of Helmate

analysis to test its employability in daily application was carried out. One study of a functional analysis to verify the metrological characterization was realized and published. Some of the following information has been presented at I2MTC 2021 – IEEE Instrumentation & Measurement Society Conference and published in:

Leopoldo Angrisani, Pasquale Arpaia, Francesco Donnarumma, Antonio Esposito, <u>Mirco Frosolone</u>, Giovanni Improta, Nicola Moccaldi, Angela Natalizio, Marco Parvis, *"Instrumentation for Motor Imagery-based Brain Computer Interfaces relying on dry electrodes: a functional analysis."*, IEEE International Instrumentation and Measurement Technology Conference (I2MTC), May 2020, (pp. 1-6). IEEE.

2.2 Experimental design

The functionality of the system is evaluated by considering the discrimination of different movement tasks, which are either executed or imagined. The final aim is to distinguish between different motor imagery tasks.

2.2.1 Reference dataset

The performance of the employed device is compared to the performance obtained by means of the same processing on a widespread dataset, namely the Brain Computer Interface Competition IV dataset 2a [83]. This dataset was created by means of a wearable cap with wet electrodes and, in this work, it is assumed as a reference for the motor imagery measurement. The dataset comprises EEG signals from 9 subjects, related to 4 classes of motor imagery. Twenty-two Ag/AgCl electrodes with conductive gel were used to record the EEG. All signals were recorded with the left mastoid serving as reference and the right mastoid as ground. The signals were sampled at 250 Sa/s and bandpass-filtered between 0.5 Hz and 100 Hz. An additional 50 Hz notch filter was applied.

2.2.2 Data processing

To distinguish between different tasks, two machine learning algorithms are adopted in this work for signal processing. Both algorithms consist of two steps, features extraction and classification. For the features extraction, a Common Spatial Pattern (CSP) algorithm is employed to enhance the signal-to-noise ratio of the EEG epochs [84]. The CSP was used as a spatial filtering algorithm. CSP is one of the most employed [85, 86]. In a binary problem, the CSP acts by calculating the covariance matrices relating to the two classes. These two matrices are simultaneously diagonalized in a way that the eigenvalues of two covariance matrices sum up to 1. Through the subsequent use of a bleaching matrix, a suitable projection matrix is identified in order to reorganize the input into a number of components consistent with the dimensions of the input matrix. In a binary problem, these components are sorted on the basis of variance in order: i) decreasing, if the projection matrix is applied to inputs belonging to class 1, and ii) ascending, in case of inputs belonging to class 2 [87] Then, two different classifiers are employed to process the brain signals, namely the Support Vector Machine (SVM), and the Random Forest. The idea behind SVM classifier is to find a hyperplane that guarantees the best separation between data points of different classes while maximizing the margin [88]. In order to deal with an eventual nonlinear separability of data, the input of the classifier is mapped to a features space with higher dimension through a “kernel function”. Usually, a “Gaussian kernel” is employed. This is also a suggested kernel for the analysis of non-stationary signals like EEG ones. Errors are allowed during separation, and the minimization of the separation error is the key for the training of this classifier.

The Random forest classifier consists of a decision tree that uses a bootstrap aggregation (bagging) ensemble procedure developed by Breiman [89]. A random forest is a collection of decision trees, each one considering a different random sample of the input. Hence, each tree is grown using a different random subset of the predictor variables to determine the binary splits. The final decision is made by considering the majority among the decisions of the trees. Usually, if p is the total number of predictors, about $\sqrt{p}$ variables are selected for each tree. The advantages in using this classifier are the low number of requested testing samples to achieve good performance, if compared to other classification algorithms. Nonetheless, it is not easy to interpret, and hence control, every aspect of the trees net [90].

2.2.3 Validation dataset

In this preliminary study, two subjects (a male and a female, both 26 years old) were enrolled. The BCI paradigm consisted of different movement tasks, either executed or imagined. Five exercises with executed and imagined movements were considered: squeeze a soft ball, dorsiflexion of the ankle, flex-extension of the forearm, finger mobilization by clenching a clothespin, and flex-extension of the leg. Every exercise can be executed with the left part of the body or the right part. In the protocol concerning the first session, for each exercise, the BCI user had to execute different trials by alternating 10 s of movement and 10 s of relax. In total 8 movement trials and 8 relax trials are executed for each exercise. The movement trials are divided by alternating a “left movement” and a “right movement”. Furthermore, 30 s of baseline are acquired at the beginning and at the end of the protocol (Fig.2.5).

The protocol concerning the second session, instead, alternates for each exercise 10 s of movement execution, 10 s of motor imagery with closed eyes, and 10 s of relax. In total 8 executed movement trials, 8 imagined movement trials, and 8 relax trials are carried on for each exercise (Fig.2.6).

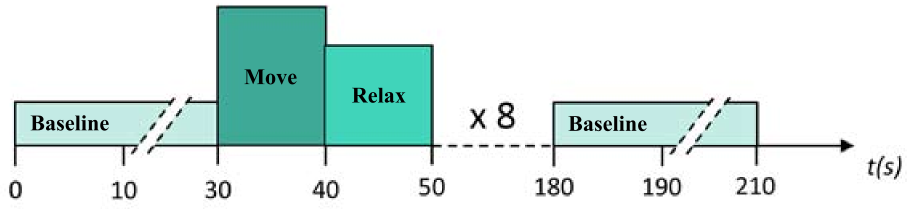


Figure 2.5: Experimental protocol of the first session: executed movement and relax tasks.

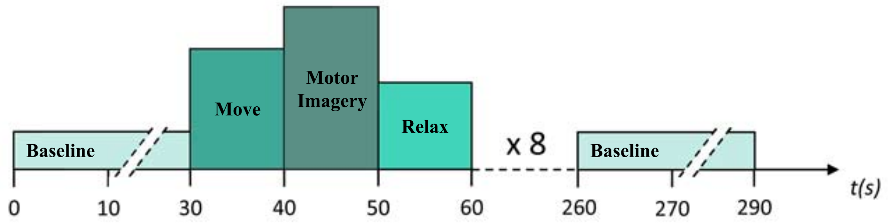


Figure 2.6: Experimental protocol of the second session: executed movement, imagined movement, and relax tasks.

2.3 Experimental results

In the present analysis, the signal processing is conducted by dividing each 10 s trials of the first session into 4 trials which are 2 s long, while the first and last second are discarded. This were done to achieve a higher number of trials, and the 2 s window was chosen as a length compatible with other experimental protocols, e.g. [83]. Thus, in this work, 64 trials are available for each exercise. Instead, from the second session, only the trials related to the imagined movements are extracted, and again each 10 s trial is divided into 4 trials which are 2 s long. The remaining data will be useful for further studies. The aim was using the Helmate to distinguish between left and right movement with different classifiers. The Helmate with dry electrodes allows the acquisition of EEG data through a dedicated software. A **.edf** file is generated for each exercise of a session. Then, a MATLAB script converts this into a .mat file by separating each trial and associating a label to them. Five different labels are possible, though the discrimination is pairwise: "relax" (R), "executed right movement" (ER), "executed left movement" (EL), "imagined right movement" (IR), and "imagined left movement" (IL). A 5-fold cross-validation was employed for the accuracy classification. The results are reported in the following tables. In Table 2.2, the distinction is conducted between a "right executed movement" (ER) and a "left executed movement" (EL).

	Subject 1		Subject 2	
	CSP+RF	*CSP+SVM*	*CSP+RF*	*CSP+SVM*
ex.1	71.7%	60.0%	57.5%	60.8%
ex.2	90.0%	72.5%	61.7%	55.8%
ex.3	72.5%	75.0%	65.0%	57.5%
ex.4	60.0%	55.8%	62.5%	59.2%
ex.5	74.1%	75.0%	70.8%	65.0%
all	70.0%	62.5%	69.4%	54.4%

Table 2.2: A right executed movement versus a left executed movement (ER vs EL).

Instead, in Table 2.3, the discrimination is conducted between a "right imagined movement" (IR) and a "left imagined movement" (IL).

	Subject 1		Subject 2	
	CSP+RF	*CSP+SVM*	*CSP+RF*	*CSP+SVM*
ex.1	72.5%	59.2%	65.8%	62.5%
ex.2	65.8%	60.0%	62.5%	36.7%
ex.3	65.0%	74.2%	63.3%	59.2%
ex.4	79.2%	55.8%	59.2%	46.7%
ex.5	79.2%	76.7%	58.3%	49.2%
all	71.9%	63.1%	64.4%	60.0%

Table 2.3: A right imagined movement versus a left imagined movement (IR vs IL).

Some important considerations can be derived from Table 2.2 and Table 2.3. The first is that, as a general trend, the two classifiers lead to compatible performance, but the Random Forest is usually better. The second important consideration is that the capability of discriminating between executed tasks is compatible with the discrimination between imagined tasks.

The Fig. 2.7 shows the results for the executed movements in a graphic way for the five different exercises. The worst exercise, in terms of accuracy, is exercise 4 (finger mobilization by clenching a clothespin), while the best exercise is number 2 (dorsiflexion of the ankle) for subject 1, and number 3 and

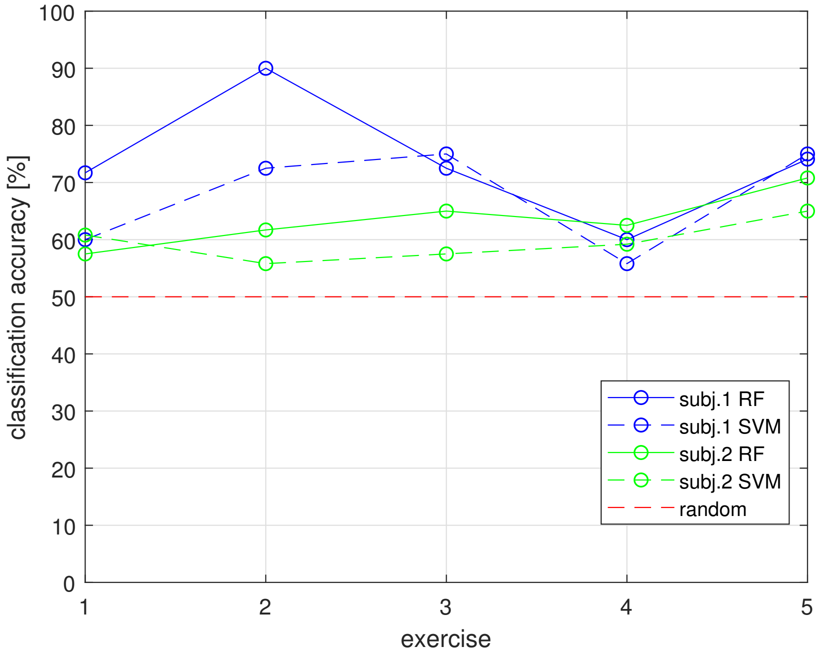


Figure 2.7: Classification accuracy for the five exercises with executed movements, considered for the two different subjects and for the two classifiers. The random classification accuracy for two tasks is also shown (red line).

5 (flex-extension of the forearm and flex-extension of the leg, respectively) for subject 2. Moreover, also for subject 1, exercises 3 and 5 are associated to a good performance. The accuracy for these tasks is about 65 % - 70 %.

The Fig. 2.8, instead, shows the results for the imagined movements for the five exercises. The overall accuracy trend is decreasing with respect to the executed movements, but some peculiarities are present. It can be seen that the SVM leads to bad performance for subject 2, which was not trained, while the Random Forest leads to almost the same accuracy value for all the exercises, i.e. around 60 % - 65 %. Instead, for subject 1, the Random Forest seems again to be preferred, and the best accuracy is reached for the imagination of the finger mobilization (exercise 4) and flex-extension of the leg (exercise 5). This accuracy is almost 80 %.

These results show that the accuracy performance depends both on the exercise and on the subject. Though the reference dataset contains data from 22 wet electrodes, only the best 8 were considered. These are the 8 electrodes that allow the best discrimination between the two abovementioned classes,

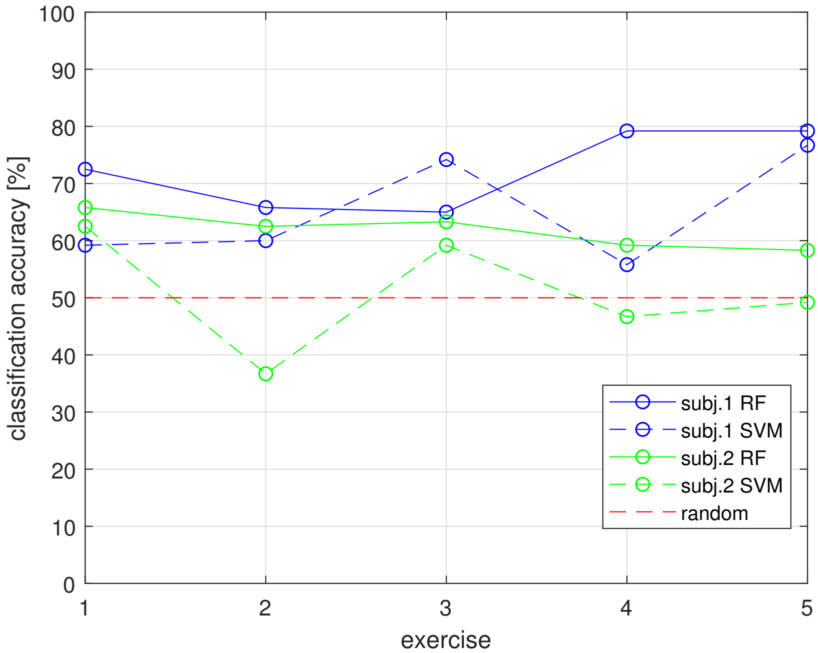


Figure 2.8: Classification accuracy for the five exercises with imagined movements, considered for the two different subjects and for the two classifiers. The random classification accuracy for two tasks is also shown (red line).

and they were selected with an iterative procedure that aimed to maximize the classification accuracy. Instead, it should be emphasized that it was not possible to directly consider the same 8 electrodes of the helmet because the reference dataset does not include the electrodes Fp1, Fp2, O1 and O2. The 5-fold cross-validation has been adopted for the 9 different subjects of the reference dataset in order to distinguish the imagination of right hand versus left hand with the Random Forest or the SVM. Depending on the subject, the classification accuracy goes from 58.2 % to 90.2 %, with an average accuracy equal to 67.5 % for the Random Forest and 71.9 % for the SVM. Moreover, it is to report that the mean classification accuracy achieved with all the 22 wet electrodes of the reference dataset [91] is about 80 %, which is still compatible with the best classification achieved with the 8 dry electrodes of the helmet. With some preliminary results, it has been shown that the achieved classification accuracy depends both on the subject and on the movement task, either executed or imagined. This accuracy goes up to 80 %, and it is also compatible with the classification accuracy obtained, in the same conditions, on a reference dataset employing wet electrodes.

The results of this work suggest that the *ab medica*® *Helmate* can be employed for the EEG health application, even though some more questions are left open for further research and development. The results of this study aim at giving a contribution to the building of wearable BCIs. In this way, the *Helmate* can be employed as a EEG system during motor task, and therefore during walk in daily life applications.

Chapter 3

Cognitive Engagement in Learning and Rehabilitation

3.1 Overview

Numerous studies evidenced that gait stability and the risk for falling are influenced by cognitive workload while walking [92]. There is a demonstrated interdependence between the gait instability and the cognitive impairment in older adults and this correlation are accepted as a factor in fall risk assessment [49]. A healthy aging process will result in loss of motor neurons, decreased nerve conduction, limited proprioception, muscle weakness, and reduced cognitive processing abilities [34]. The ability to quickly re-weight sensory information and adapt to environmental changes are significantly reduced in the older due to a decline in cognitive processing abilities[35]. A lack of ability to adapt to environmental changes efficiently and effectively may be a contributing factor in the gait instability among a geriatric population. However, the differences between gait of younger and older adults are manifold [34]. The factors behind the gait are various, and those described above contribute only partially to the gait and the risk of falling. Gait is a complex procedure and requires the naturally use of executive functions, high attention in the presence of concurrent tasks, and also an increased working memory (which in turn requires a significant cognitive engagement) [11]. It has been shown that at an increased in load of cognitive activity, the subjects tend to exhibit modifications to their gait (for example a slowing, or a reduction of the stride as a compensatory action). Montero et al. sustained that the greater is the cognitive load the subject experiences while performing a dual-task paradigm during walking, more the subject is at risk of falling [49]. In recent years, the literature has been opening up to the study of cognitive load in a broader context: the cognitive load associated to the concept of *engagement*.

The term engagement, derived from the verb *engager*, and it is often used as a synonym for involvement and/or commitment. The engagement has a multi-dimensional and heterogeneous nature. Several definitions have been provided over the years because of this reason. The engagement has been analyzed in many different areas. In this thesis, we focused on two fields: the engagement in pediatric rehabilitation, and engagement in the learning. In rehabilitation, Graffigna et al. defined patient engagement as a "multi-dimensional psycho-social process, resulting from the conjoint cognitive, emotional, and behavioral enactment of individuals toward their health condition and management" [93]. Gross et al. showed the effectiveness learning process mainly depends on the engagement level of the learner [94]. In this context, *engagement* stands for concentrated attention, commitment, and active involvement in contrast to apathy, lack of interest or superficial participation [95, 96]. A difficult task will consume most of the cognitive capacities and therefore make it difficult to perform successfully on other, unrelated tasks. With a higher cognitive load, the effort expended on a difficult task can consume attention, reducing the cognitive capacity to process painful stimuli [97]. In work, play, and social interaction, we may experience varying levels of engagement as we talk, listen, observe, read, reflect, and use our bodies [98].) In the learning context, Fred Newman, in his report "Student Engagement and Achievement in American Secondary Schools", defines engagement as: "the student's psychological investment in and effort directed toward learning, under-standing, or mastering the knowledge, skills, or crafts that academic work is intended to promote" [98, 99]. Moreover, in 1990, Kahn based the definition of engagement on three broad dimensions: behavioural, cognitive, and emotional [100]. Behavioral engagement is the set of observable indicators (postures, gestures, actions, etc.) of persistence and participation. Cognitive engagement is the effort to extend one's intellectual commitment beyond the minimum required to complete the task. Finally, emotional engagement is the positive emotional reactions of individuals to a task. Lequerica et al. defined engagement in rehabilitation as "a deliberate effort and commitment to working toward the goals of rehabilitation interventions, typically demonstrated through active, effortfull participation in therapies and cooperation with treatment providers" [101]. The cognitive dimension refers to the patient understanding of his/her existing condition, of the possible diseases course, of the necessary treatments and of its continuous monitoring. The emotional dimension is connected to the emotional reactions of patients in adapting to the onset of the disease and to the possible new life conditions related to it. T he behavioral dimension consists of all the activities that the patient decides to implement (together with the medical team) to deal with the disease and treatment. As concerns the engagement assessment, evaluation grids, and self-assessment questionnaires (to be filled out by the observer or by the learner autonomously) are traditionally the most used methods for the behavioral, the cognitive, and the emotional engagement detection [102]. In recent years, measures based on biosignals are spreading very rapidly. Furthermore, the use of physiological sensors able to detect cognitive and emotional engagement allows the real-time machine adaptive strategies. Among the different physiological biosignals, the EEG appears to be one of the most promising technology thanks to its low cost, low invasiveness, and high temporal resolution. Moreover, the EEG contains a broader range of information about the state of a subject with respect to others biosignals [103].

In 1995, authors in [104] proposed an engagement index to decide when to use the autopilot and when to switch to the manual one during a fly simulator session. The engagement index was $E = \frac{\beta}{\theta+\alpha}$ where α, β, and θ are the EEG frequency bands in (8-13) Hz, (13-22) Hz, and (4-8) Hz respectively. Several studies used this index as engagement estimator [105, 102, 106]. However, the proposed index does not consider the different engagement dimensions (i.e., cognitive, emotional and behavioural) proposed by the theories previously reported. Increased cognitive load, and therefore in the cognitive engagement, leads to impaired mobility decisions and a risk for falls [107].

To evaluate the importance of cognitive engagement in these two contexts, two studies were realized:

I **Andrea Apicella, Pasquale Arpaia, Mirco Frosolone, Giovanni Improta, Nicola Moccaldi, Andrea Pollastro, *"EEG-based Measurement System for Student Engagement Detection in Learning 4.0."*, submitted to Scientific Reports, 2021.**

II **Pasquale Arpaia, Fabio D'Asaro, Mirco Frosolone, Marco Grazioso, Giovanna Mastrati, Nicola Moccaldi, Luca Raggioli, Silvia Rossi, *"Data-fusion based adaptive rehabilitation system: a pilot study."*, to be submitted to User Modeling and User-Adapted Interaction, 2021.**

3.2 Cognitive engagement: Learning context

Some of the following information are available in **I**.
In the first study, a wearable system for the personalized EEG-based de-

tection of engagement in learning 4.0 is proposed. The system can be used to make an automated teaching platform adaptable to the cognitive load and emotional conditions of the user, and the system proposed can be used to detect cognitive engagement. When a subject learns a specific pattern, the *neuroplasticity process* is activated modifying the neural brain structure [108]. Once the process is learned, the brain builds a myelinated axon connection system to automate that. The adjacent neurons fire in unison, and more the experience or operation is repeated, more the synaptic link between neurons becomes strong [109]. The automated use of all mental processes as well as the understanding and use of new technologies occurs through the creation of neural diagrams and maps [110, 111]. During life, humans learn new skills or modify the already learned ones by enriching the existing neural maps. Therefore, the introduction of increasingly innovative technologies requires a continuous brain re-adaptation to new interfaces [112]. The brain synaptic structure is modified to learn new (or different) basic skills in order to perform tasks previously performed differently. This effort is more effective when the learner is engaged. An engaged user actuates learning in an optimal way, avoiding distractions, and increasing the mental performance [113, 114].

To achieve a correct metrological reference of the EEG-based cognitive and emotional engagement constructs, a reproducibility problem arises. From emotional point of view, when eliciting a specific emotion, the same stimulus does not often induce the same emotion in different subjects. The effectiveness of the induction can be verified by means of self-assessment questionnaires or scales. The combined use of standardized stimuli and subject's self-assessment ratings can be an effective way to build a metrological reference for a reliable EEG-based emotional engagement detection [115]. From the cognitive point of view, when the subject is learning, the working memory identifies the incoming information and the long-term memory constructs and stores new schemes on the basis of the past ones. While the already built schemes decrease in the working memory load, the construction of new schemes entails its increase [103, 116]. Therefore, increasing difficulty levels allows to induce different cognitive states; the cognitive engagement level grows up according to the proposed exercise difficulty increases.

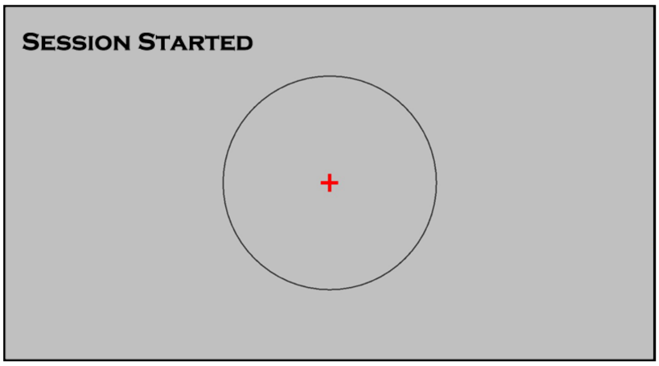
3.2.1 Experimental design

Twenty-one school age subjects (9 males and 13 females, 23.7 ± 4.1 years) participated in the experiment. All volunteers have no neurological diseases. The ethical committee of the University of Naples Federico II approved the experimental protocol of this study. All methods were performed in accordance with the relevant guidelines and regulations. Before the experiment, each subject read and signed the informed consent. Each subject was seated in a comfortable chair at a distance of 1 m from the computer screen. The location was sanitized before and after of each acquisition as indicated in the COVID-19 academic protocols. Each subject was equipped with a mouse to carry out the experimental test. After wearing the EEG-cap, the contact impedance was assessed to guarantee optimal signal-acquisition conditions (see 2). Each subject underwent an experimental session composed by 8 trials. Various stimuli to induce high and low levels of emotive and cognitive engagements were equally distributed among the trials. As stimulus modulating the cognitive engagement level an updated and revised Continuous Performance Test (CPT) [117] was administrated. In particular, a CPT version based on a learning by doing activity on how an interface works was adopted. Whereas, proper background music and social feedback was used to modulate the emotive engagement level . More in details, the three different stimuli are described as follows:

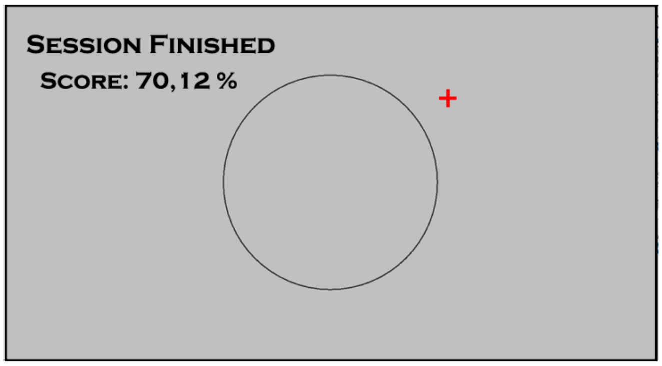
- *Revised CPT:* a red cross and a black circle on the computer screen were presented to the subject. The red cross tends to run out from the circle on the screen in random directions. The subject was asked to keep the cross inside the circle by using the mouse. For each trial, a different difficulty level was set by the experimenter changing the cross speed. The percentage of the time spent by the red cross inside the black circle with respect to the total time was reported to the subject at the end of the trial (Fig. 3.1).

- *Background music:* for each trial, a particular emotive engagement level was favored by proper background music. The music tracks were randomly selected from the MER [118] database where songs are organized according to the 4 quadrants of the emotion Russell's circumplex model [119]. The songs associated with the Q1 and Q4 quadrants (*cheerful music*) were employed in high emotional engagement trials, Q2 and Q3 for the low ones (*sad music*).

- *Social feedback:* during each trial, the experimenters gave proper social feedback according to the emotive engagement levels under the experimental protocol. The positive and negative social feedback consisted of encouraging and disheartening comments respectively, given to subject on his/her ongoing performance. The choice of social feedback to use was made by a group of psychologists. The social feedback effectiveness was improved by the simultaneous music background effects.



(a) Session Started



(b) Session Finished

Figure 3.1: Screen shots from the CPT game. At the beginning of the game (a),the cross starts to run away from the center of the black circumference. The user goal is to bring the cross back to the center by using the mouse. At the end of each trial (b), the score indicates the percentage time spent by the cross inside the circumference.

A well-founded metrological reference, is ensured by two assessment procedures validating the stimuli effectiveness were used:

- *performance index*: an empirical threshold was used to confirm that an appropriate CPT stimuli response was given by the participant. The threshold changed according to the trial difficulty level.

- *Self Assessment Manikin questionnaire (SAM)*: the emotional engagement level was assessed by a 9-level version of the SAM. The lower emotional engagement level was associated to the SAM score 1, while the greater one to 9 [120].

The experimental session started with the administration of the SAM to

Table 3.1: Trials description - for each trial the positiveness/negativeness of the background music, the randomly movement speed of the cross, and the duration in second are reported.

# Trial	Background Music	Speed [px/s]	Duration [s]
1	Positive	50	50
2	Negative	75	120
3	Positive	100	45
4	Positive	150	45
5	Positive	300	45
6	Negative	700	45
7	Negative	800	45
8	Negative	900	120

get information about the initial emotional condition of the subject. Then, a preliminary CPT training phase to uniform all the participants starting levels was realized. After this preliminary phase, each trial was implemented by a succession of a CPT stage followed by a SAM administration. The description of trials organization is described in Table 3.1. The background music, the movement speed of the cross, and the duration of each trial are shown. and the music, speed and duration parameters are showed in Table 3.1.

The *ab medica*® *Helmate* system is employed for the EEG signal measurements [80] (Fig. 3.2).

Figure 3.2: EEG-signal acquisition device Helmate from *ab medica*[80]

3.2.2 Data processing

Forty-five seconds of acquisition EEG signals were labeled according to two parameters: i) high or low emotional engagement, and ii) high or low cognitive engagement. More in detail, regarding the cognitive engagement, the trials were labeled according to the CPT speed [121, 116], since the higher was the speed the more the cognitive engagement increased [103, 116]. The trials having speed lower than 150 pixels/s were labeled as low_c whereas $high_c$, were assigned to the trials having speed higher than 300 pixels/s. As concern the emotional engagement, the trials characterized by cheerful/sad music and positive/negative social feedback were labelled as $high_e/low_e$. For each trial, the SAM results (normalized to the initial pre-session value) were consistent with the proposed stimuli. In fact, a one-tailed t-student analysis revealed in the worst case a 0.02 P-value.

An artifact removal stage preceded the feature extraction and the classification stages. The Independent Component Analysis (ICA) was used to filter out the artifacts from the EEG signals using the *Runica* module of the EEGLab tool [122]. Then, data were normalized by subtracting their mean and dividing for their standard deviation. EEG data were divided in epochs of 3 s, overlapping by 1.5 s. Owing to the sampling rate of 512 Sa/s, for each subject 232 epochs of 1536 samples per channel were extracted.

Five different strategies were compared:

1. *Butterworth - Principal Component Analysis* (BPCA): data were filtered by a fourth-order bandpass Butterworth filter [0.5 - 45] Hz; then, relevant features were extracted using Principal Component Analysis (PCA)[123] selecting the components explaining the 95% of the total variance;

2. *Butterworth - CSP* (BCSP): data were filtered using a fourth-order bandpass Butterworth filter [0.5 - 45] Hz followed by a CSP projection stage;

3. *Filter Bank - CSP* (FBCSP): data were filtered through a 12 IIR bandpass Chebyshev filter type 2 filter bank with a 4 Hz bandwidth equally spaced from 0.5 to 48.5 Hz, followed by a CSP projection stage.

4. *Domain adaptation*: only in the cross-subject approach, a baseline removal and a TCA were adopted.

5. *Engagement Index*: to make a comparison with the classical literature approach, the engagement index proposed in [104] was extracted.

Although the Engagement Index was not defined for a particular engagement type, given the experimental setup proposed in [104], it can be assumed compatible with the cognitive engagement proposed in this work.

Two different approach was implemented: within-subject, and cross-subject. A cross-subject approach has several advantages with respect to a within-subject one, such as the reduction of time for the initial calibration procedure. Unfortunately, the non-stationarity nature of the EEG signal leads to a greater data variability between subjects. This is a well-known problem in the literature, which makes the cross-subject approach a very challenging task [124]. Currently, the Domain Adaptation methods [125] are obtaining a great attention from the scientific community. In this work, the Transfer Component Analisys (TCA) [126] is adopted. The TCA is a well-established technique of domain adaptation already used in the EEG signal classification literature with promising results [124]. In a nutshell, TCA searches for a common latent space between data sampled from two different (but related) data distributions by preserving data properties. More in detail, TCA searches for a data projection ϕ that minimizes the *Maximum Mean Discrepancy* (MMD) between the two distributions, that is:

$$||\frac{1}{n_S}\sum_{i=1}^{n_S}\phi(\vec{x}_{Si}) - \frac{1}{n_T}\sum_{i=1}^{n_T}\phi(\vec{x}_{Ti})||^2$$

where n_S and n_T are the numbers of points in the first (*source*) and the second (*target*) domain set respectively, while $\vec{x}_{S_i}$ and $\vec{x}_{Ti}$ are the $i-$th point (epoch) in the two different sets. The data projected in the new latent space are then used as input for the classification pipeline. However, TCA works with only two different domains, differently from a multiple-subject environment, which can lead to a domain composed of several sub-domains generated by the different subjects or sessions. In [124], TCA was tested by considering for the first domain a subset of samples from $N-1$ subjects, where N is the total number of subjects, and with the data of the remaining subject for the other domain. However, this approach does not take into consideration the fact that different subjects may belong to very different domains, leading to poor results. A simple solution consists in subtracting to each subject a baseline signal recorded from the user, for example, in rest condition. However, this last point requires new subject acquisition. Instead, in this work, an average of the signals for each subject is used as baseline, thus avoiding the need for new signal acquisitions. The output of the classification stage can be "high" or "low" both for cognitive and emotional engagement. For each feature selection strategy shown in the previous subsection, four different classifiers were compared: Support Vector Machine (SVM), k-Nearest Neighbors (k-NN)[127], shallow Artificial Neural Networks (ANN)[128], and Linear Discriminant Analysis (LDA)[127]. Each combination of feature selection strategies and classifiers were used on both emotional, and cognitive engagement.

The best model was selected by a *stratified leave-2-trials out* technique in order to maintain a balancing among the classes in each fold. A *Grid search* strategy was adopted as approach for hyperparameters tuning for each classifier (Table 3.2).

3.2.3 Experimental results

Two different approach are evaluated in this work: a within-subjects, and a cross-subject approach.

Within-subjects approach

Firstly, to make a comparison with the classical literature approach, the engagement index proposed in [104] was used as feature for a classification of the cognitive engagement. Unfortunately, as highlighted by the results reported in Table 3.3 accuracy performances were not optimal. In fact, this feature is mainly used in non-predictive applications (e.g., [106]).

Instead, the best results both on cognitive and emotional engagements (Fig. 3.3) were achieved using features extracted by Filter-Bank and CSP. Quantitative results related to the use of Filter Bank and CSP for each classifier can be observed in Table 3.4: among the different classifiers, SVM stands out with a better performance than the others, reaching its best mean accuracies of 76.9 ± 10.2 % on cognitive engagement classification and of 76.7 ± 10.0 % on emotional engagement. Results are computed as the average accuracy over all the subjects.

The results reported in Fig. 3.3b show that the Filter Bank improves the classification performance in a significant way. This can be due to the use of several sub-bands which highlight the signal main characteristics, allowing the CSP computation to project the subject data in a more discriminant common space. In Fig. 3.4, BCSP and FBCSP are compared through t-SNE [129] on the subject data transformed using the two different methods. The figure shows that, for several subjects, CSP applied after FB projects the data in a space where they are easily separable with respect to the BCSP case.

Cross-subject approach

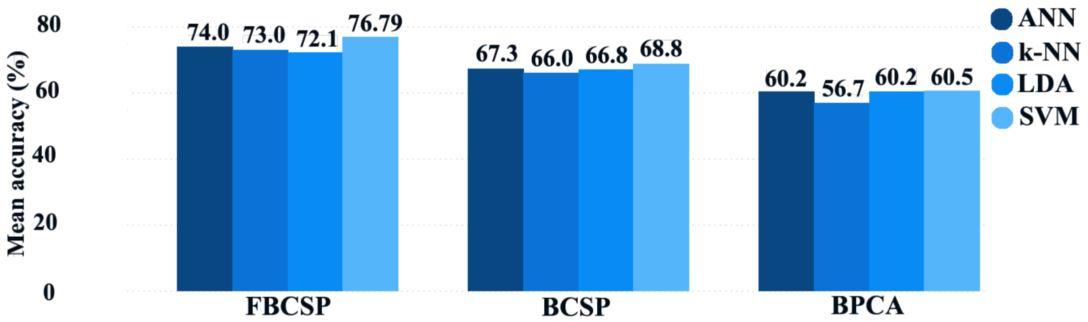
A t-SNE plot of the data first and after removing the average value of each

Table 3.2: Classifier optimized hyperparameters and variation range.

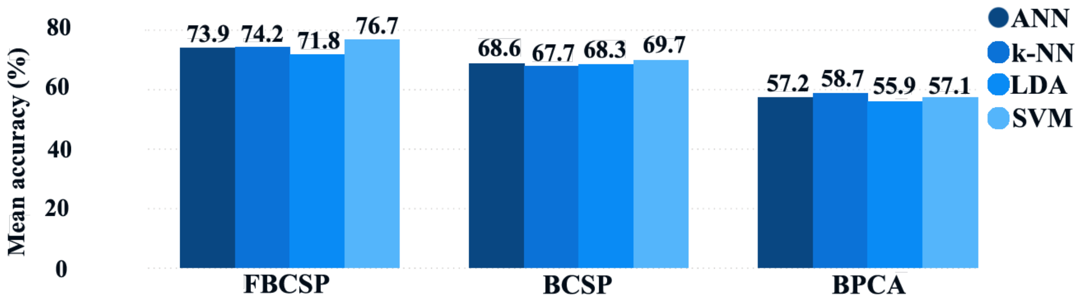
Classifier	Optimized Hyperparameter	Variation Range
k-Nearest Neighbour (k-NN)	Algorithms	{Ball tree, KD Tree, Brute Force}
	Distance Weight	{equal, inverse}
	Num Neighbors	[1, 10], step: 1
Support Vector Machine (SVM)	C Regularization	{0.01, 0.1, 1, 5, 10}
	Kernel Function	{radial basis, polynomial}
	Polynomial Order	{2, 3}
Artificial Neural Network (ANN)	Activation Function	{ReLU, sigmoid}
	Hidden Layers nr. of Neurons	[5, 50], step: 25
	Learning Rate	{0.001, 0.01}
Linear Discriminant Analysis (LDA)	Solver	{Singular Value Decomposition, Least Squares}
	Shrinkage	{None, Ledoit-Wolf lemma}

Table 3.3: Within-subject experimental results. Classification accuracies using the *Engagement Index* [104] for cognitive engagement classifications are reported.

Method	Cognitive Engagement
SVM	54.8 ± 4.9
k-NN	53.7 ± 5.7
ANN	53.1 ± 5.4
LDA	50.7 ± 6.2



(a) Cognitive engagement



(b) Emotional engagament

Figure 3.3: Within-subject performances of the compared processing techniques in (a) cognitive engagement and (b) emotional engagement detection. Each bar describes the average accuracy over all the subjects.

subject is shown in Fig. 3.5. The data without for-subject average removal (Fig. 3.5 a) are disposed in several clusters over the t-SNE space, exhibiting a fragmentation tendency. Instead, after the for-subject average removal (Fig. 3.5b), the data result more homogeneous, enhancing the model generalizability. A comparison using TCA with and without the for-subject average

Table 3.4: Within-subject experimental results. Accuracies are reported on data preprocessed using Filter Bank and CSP for cognitive engagement and emotional engagement classifications. The best performance average values are highlighted in bold.

Method	Cognitive Engagement (proposed)	Emotional Engagement (proposed)
k-NN	73.0 ± 9.7	74.2 ± 10.3
SVM	**76.9 ± 10.2**	**76.7 ± 10.0**
ANN	74.0 ± 9.2	73.9 ± 9.1
LDA	72.1 ± 11.4	71.6 ± 9.3

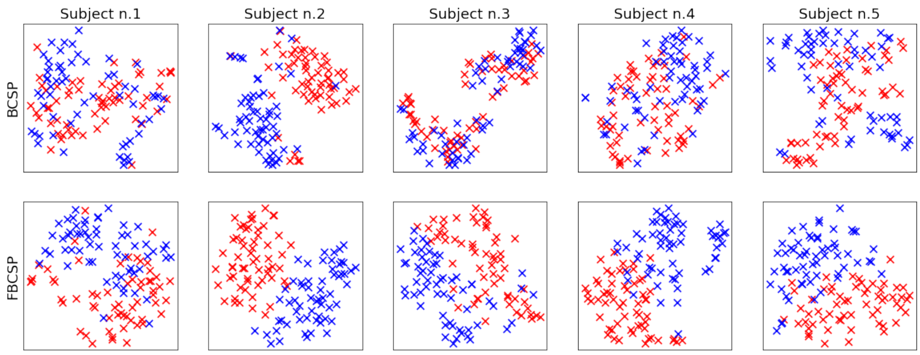


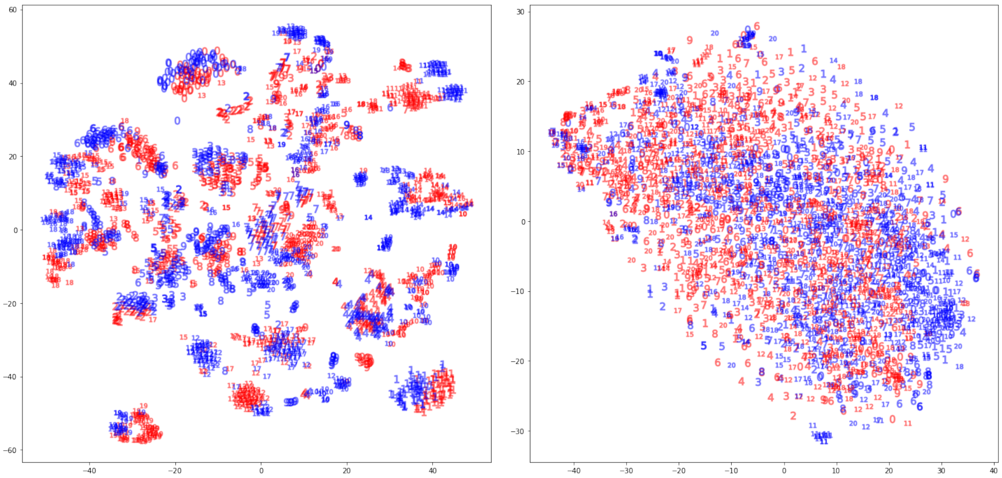
Figure 3.4: Filter Bank impact on the class (red and blue points) separability. t-SNE-based features plot of five subjects randomly sampled (first row: without Filter Bank; second row: with Filter Bank).

removal is made and the resulting performances are reported in Table 3.5. The results show that removing the for-subject average from each subject boosts the performance with respect to using TCA alone (more than 3 % of improvement in almost all classifiers, especially in Cognitive Engagement case).

In this work, a wearable system for personalized EEG-based cognitive and emotional engagement detection is proposed. The system can be used in the context of Learning 4.0. The system is validated on students during a training stage involving cognitive and motor skills and aimed to learn how to use a human-machine interface. Standard stimuli, performance indicator, and self assessment questionnaires were employed to guarantee a well founded metrologically reference. The proposed method, based on Filter Bank, CSP and SVM, experimentally showed the best performance. In particular, in the cross-subject case, an average accuracy of 72.8 % was reached for the cogni-

Method	**With For-Subject Average Removal**		**Without For-Subject Average Removal**	
	Cognitive Engagement	**Emotional Engagement**	**Cognitive Engagement**	**Emotional Engagement**
SVM	**72.8 ± 0.11**	**66.2 ± 0.14**	64.0 ± 0.11	61.7 ± 0.10
k-NN	69.6 ± 0.11	61.9 ± 0.09	57.1 ± 0.09	56.9 ± 0.10
ANN	72.6 ± 0.12	65.7 ± 0.14	69.7 ± 0.12	65.8 ± 0.15
LDA	69.5 ± 0.12	65.3 ± 0.14	69.6 ± 0.13	64.6 ± 0.13

Table 3.5: Cross-subject experimental results using FBCSP followed by TCA. Accuracies are reported with and without for-subject average removal for cognitive engagement and emotional engagement detection. The best performance values are highlighted in bold.



(a) **(b)**

Figure 3.5: A comparison using t-SNE of the FBCSP data first (a) and after (b) removing the average value of each subject, in the cross-subject approach.

tive engagement by using TCA and for-subject average removal. Instead, in the within-subject case, an accuracy of 76.9 % was reached.

3.2.4 Proposed Method

The proposed method is depicted in Fig. 3.6. The eight *Active Dry Electrodes* acquire the EEG signals directly from the scalp. Each channel is differential with respect to AFz (REF), and referred to Fpz (GND), according to 10/20 international system. After transduction, analog signals are conditioned by the *Analog Front End*. Next, they are digitized by the *Analog Digital Converter* (ADC), and submit an *Artifact removal block* performed by an ICA based algorithm. Then the signals are sent by the wireless Bluetooth transmission to the *Data Processing* stage. Here, the suitable feature are extracted by a 12-component *Filter Bank*. The two *Support Vector Machine* (SVM) classifiers receive the features array from two trained *Common Spatial Pattern* (CSP) algorithms for detecting the Cognitive and the Emotional Engagement respectively. Only in the cross-subject case, a baseline removal followed by a TCA procedure is provided during the training stage of the classifier.

These results are important steps for cognitive engagement detection and to evaluate the related cognitive load in everyday conditions. This is an important first step to be able to analyze the effect of the working memory

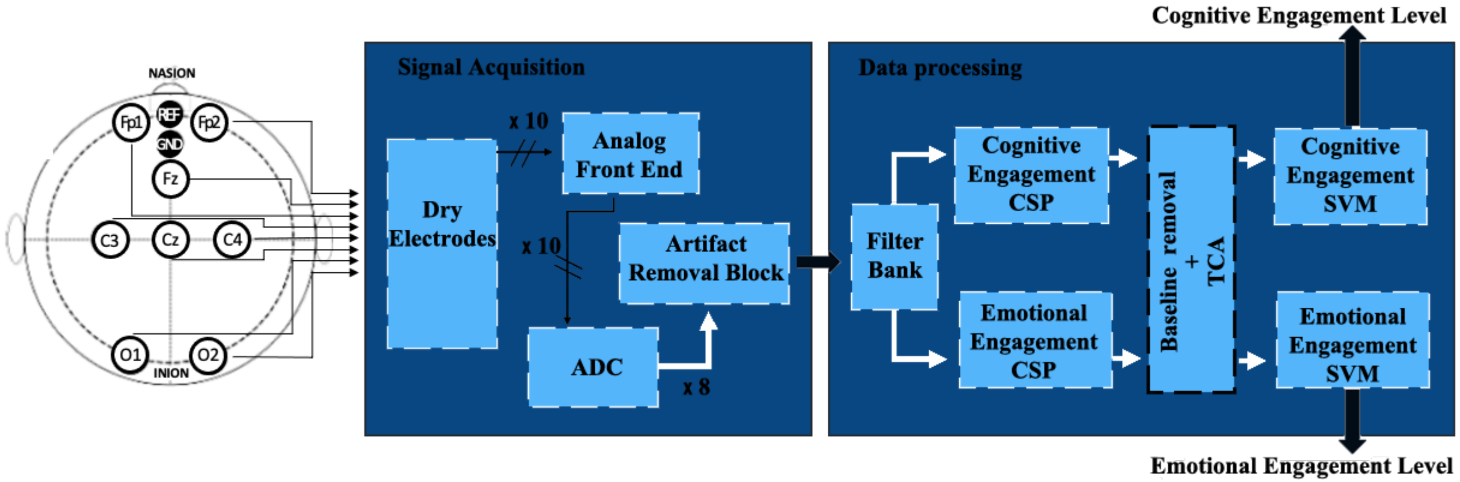


Figure 3.6: The proposed distraction-detection method (CSP: Common Spatial Pattern algorithm).

and cognitive load during the gait analysis.

3.3 Cognitive engagement: Rehabilitation context

Some of the following information are available in **II**.

In the second study, a wearable system for the personalized EEG-based detection of engagement in in neuro-motor rehabilitation is proposed. Engagement assessment is fundamental in clinical practice to personalize treatments and improve their effectiveness. The adaptivity in motor rehabilitation traditionally concerns the possibility of an automated system to adequately stimulate the residual motor skills of a patient: not a little otherwise it does not strengthen, not too much otherwise the exercise becomes impractical. Often, the optimal level of stimulation is found by analyzing the user's performance in real time and adaptation techniques only focus on maximising effort during the rehabilitation session [130, 131, 132, 133]. Although a significant amount of work has been done in the general area of motor rehabilitation with promising results [134], there is still a need for developing personalised therapeutic scenarios. Recently, another way of looking at adaptivity is emerging. The focus is not only on the user's performance, but also on her/his mental condition. For example, some studies have focused on levels of cognitive engagement during robotic motor rehabilitation [135]. The basic idea is to adapt an automated rehabilitation system to the user's current condition, maximizing her/his sustained attention to the proposed motor activity. The attention to the motor task, in fact has an enhanced effect on the rehabilitation effectiveness [136]. In the present work, a module for cognitive and emotional engagement assessment, designed to be integrated into an automated [137] or semi-automated [138] rehabilitation system, is presented. This module is insert in a data-driven method. Data-driven methods are effectively deployed to recognize complex activities. However, they lack the capability of capturing important semantic relationships between sensor events and activities that could be easily expressed through the use of knowledge-based approaches. The proposed framework allows multiple data from heterogeneous sensors to be integrated by the combination of data-driven and knowledge-based reasoning techniques.

3.3.1 Experimental design

Three males and one female aged between 5 and 7 years were selected for the experiment. Each participant suffering from disturbances in motor-visual coordination (double hemiplegia, severe neuropsychomotricity delay in spastic expression from perinatal suffering, neuropsychomotricity delay, and motor skills deficit with dyspraxiam). The ethical committee of the University Federico II approved the experimental protocol. An informed consent were signed by families agreed to the experimental activities. All the experimental procedures were performed according to guidelines and regulations [139]. The Perfetti-Puccini method (also known as Cognitive Therapeutic Exercise) was adopted as therapeutic approach [140]. The aims of this methods is to recover the injury and activate the brain circuits governing the movement. A visual attention exercise was performed by each participant; the correct posture of the trunk, neck, and head were required. The participant were seated on a comfortable chair and a screen was placed at the eye level of the subject (Fig. 3.7).

Figure 3.7: Neuromotor rehabilitation session.

The participants could choose four different characters before starting exercise: a bee, a ladybug, a girl, or a little fish. The child had to stare at the character on the screen to make it move while maintaining eye contact. The parameters setting during the game were: (i) the movement direction of the character (from left to right or vice versa, or from up to down and vice versa), and (ii) the background landscape. To improve the participant engagement, a background music was played during the game. Several professional figures supervised to all phases of the experimental activity: physiotherapists, bioengineers, software engineers, psychologists, doctors specialist.

The system architecture is shown in Figure 3.8. It is composed of a Rehabilitation Game Platform and an Engagement Detection Component.

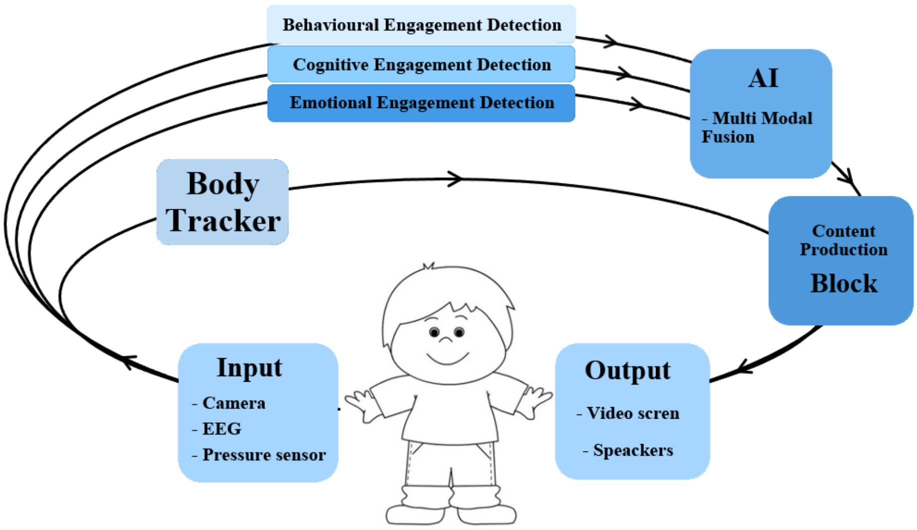


Figure 3.8: Three-dimensional system architecture

The content production module updates the audio-visual stimuli as a function of three sets of inputs related to the evaluation of Behavioral, Cognitive, and Emotional engagement. The first set of inputs is related to Behavioral engagement. It provides information about the user's head pose and is detected in real time by a body tracker on the basis of the images acquired by the video camera. The second set of input contains the information about the emotional engagement evaluated on the basis of the data supplied by the camera and the EEG headset. Finally, cognitive engagement is detected employing the EEG data. A data-driven approaches proved to be promising for an effective processing of the EEG signal. Thus, an EEG-based system for cognitive engagement detection is proposed. A wearable, low cost device is adopted to acquire the EEG data: emotiv epoc+ (Fig. 3.7). Two cameras video-recorded each session (by front and side framing). The Pediatric Assessment of Rehabilitation Engagement (PARE) scale was employed for labeling the EEG signals. The emotional and cognitive engagement were separately examined. A multidisciplinary team evaluated each session by viewing the videos. Two levels emotional engagement and cognitive engagement are identified: high and low. The consensus among the raters was statistically analyzed and reached the 95.2 % [141]. The teams evaluations were employed as ground-truth to label the EEG dataset.

3.3.2 EEG Data processing

Each subject underwent five EEG recording sessions of 15 min. The EEG signal was divided in epochs of 9 s. A total of 1121 epochs were acquired, and 280 ± 46 epochs for each participant. The different number of epochs was due to a less constrained experimental protocol, adopted to ensure a greater comfort for the patients. Th k-Nearest Neighbors (k-NN), the Support Vector Machine (SVM), and the Artificial Neural Network (ANN) were employed as machine learning classifiers. A grid search CV procedure was implemented to found the best parameters model. The hyperparameters values for each classifier model are reported in Table 3.6.

The data were processed considering the same temporal order of acquisition; the first 70 % of the data of each session was employed as a training set and the remaining 30 % as a test set. Such a subdivision into training and test sets for intra-individual classification is widely used in literature for EEG data [142, 143, 144]. To manage the test data, in case of imbalanced test data, the balanced accuracy (BA [145]), and the the Matthew correlation coefficient (MCC [146]) were used as performance scores. In fact, the standard accuracy are unreliable since they can be biased toward the dominant class [147]. The BC provides a classification performance measure more efficient in case of imbalanced data condition; the MCC gives a correlation measure between the observed data and the predicted classifications [148]. In particular, MCC and BA are defined as:

$$BA = \frac{1}{2}\left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP}\right) \tag{3.1}$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \tag{3.2}$$

where respectively, TP are the true positives, TN are the true negatives, FP are the false positives, and FN are the false negatives (where positive and negative referred to the low and the high values of the engagement). The BC is defined in the range $[0, 1]$ (as accuracy); the MCC in the range $[-1, 1]$, where 1 means a perfect prediction, 0 a random prediction and -1 means a total misclassification.

3.3.3 Experimental results

The overall means of the intra-individual balanced BC and MCC scores for the three classifiers for the cognitive engagement are reported in Table 3.7.

As can be seen from the results, oversampling improved the results achieved, especially when the KMeansSMOTE method was employed. The

Table 3.6: Classifiers, optimized Hyperparameters, and variation ranges.

Classifier	Optimized Hyperparameter	Variation Range
k-Nearest Neighbour (k-NN)	Distance	{minkowski, chebychev, manhattan, cosine, euclidean}
	Distance Weight	{equal, inverse, squaredinverse}
	Num Neighbors	[1, 7] step: 1
Support Vector Machine (SVM)	C Regularization	{0.1, 1, 5}
	Kernel Function	{radial basis, polynomial}
	Polynomial Order	{1, 2, 3}
Artificial Neural Network (ANN)	Activation Function	{relu, tanh}
	Hidden Layer nr. of Neurons	[5, 505] step: 20
	Learning Rate	{0.0005, 0.0001, 0.001, 0.005, 0.01}

Table 3.7: Overall mean of the intra-individual performances on cognitive engagement using three different classifiers (k-NN, SVM and ANN): the balanced accuracy (BA) and the Matthews correlation coefficient (MCC) at varying the oversampling methods.

Oversampling	**Metric**	**k-NN**	**SVM**	**ANN**	**Mean**
none	BA	67.1	67.4	73.7	69.4 ± 3.0
	MCC	0.31	0.34	0.45	0.36 ± 0.06
SMOTE	BA	68.6	69.8	72.0	70.1 ± 1.4
	MCC	0.33	0.36	0.40	0.36 ± 0.03
BorderlineSMOTE	BA	70.3	70.9	73.6	71.6 ± 1.4
	MCC	0.36	0.38	0.43	0.39 ± 0.03
ADASYN	BA	68.1	68.3	72.5	69.6 ± 2.0
	MCC	0.33	0.33	0.42	0.36 ± 0.04
SVMSMOTE	BA	69.0	69.4	72.9	70.4 ± 1.7
	MCC	0.34	0.36	0.42	0.37 ± 0.03
KMeansSMOTE	BA	69.8	71.1	74.5	$\mathbf{71.8 \pm 1.98}$
	MCC	0.35	0.39	0.46	$\mathbf{0.39 \pm 0.04}$

BC performance of the three classifiers using the KMeansSMOTE method for each subject are reported in Fig. 3.9.

3.3.4 Proposed Method

The proposed method is illustrated in Fig. 3.10. The emotiv epoc+ *semi-wet 14 electrodes* allows the EEG signals to be sensed directly from the scalp of the child. The CMS/DRL referred all the channels. The analog signal are firstly conditioned by an internal system amplification and filtering (*Analog Filter and Amplifier*). Then, they are digitized by the Analog Digital Converter *ADC* and sent by the *Wireless Transmission Unit* to the *Data Processing* block. The *Classifiers* receive the feature arrays from two trained *Common Spatial Pattern* procedures for detecting the cognitive and emotional engagement.

The proposed method, based on KMeansSMOTE technique, showed experimentally a mean balanced accuracy of 74.5 % for cognitive engagement detection. This method was then introduced into the game system. Based on the information coming from the various sensors, a the decision making block was implemented. The action language *Epistemic Probabilistic Event Calculus* (*EPEC* for short) [149] was able to make online decisions as the

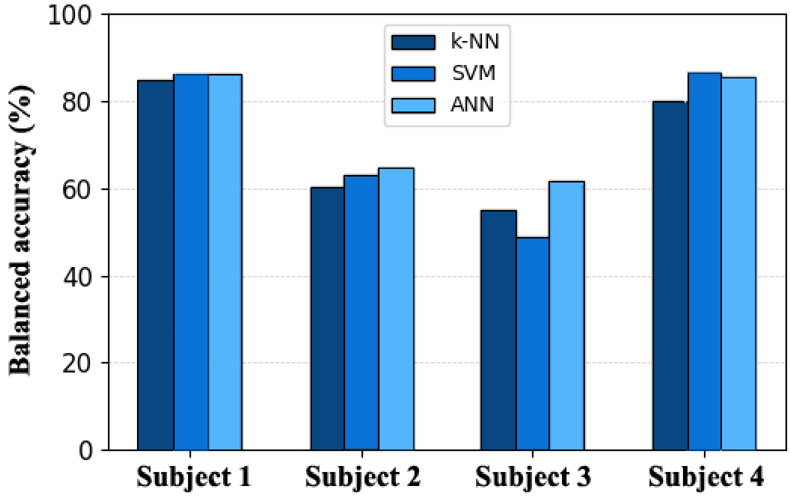


Figure 3.9: Cognitive engagement balanced BC performance for each subject based on KMeansSMOTE oversampling technique. Classifier performances are reported: k-NN (black), SVM (grey), ANN (white).

child is performing the exercise. An assessment of the acceptability of the system was conducted by directly evaluating the cognitive and emotional engagement levels of the child. The Fig. 3.11 shows the time-trends of the cognitive engagement of one subject during all the sessions. The high levels of cognitive engagement highlight the acceptability by the subjects of the proposed method.

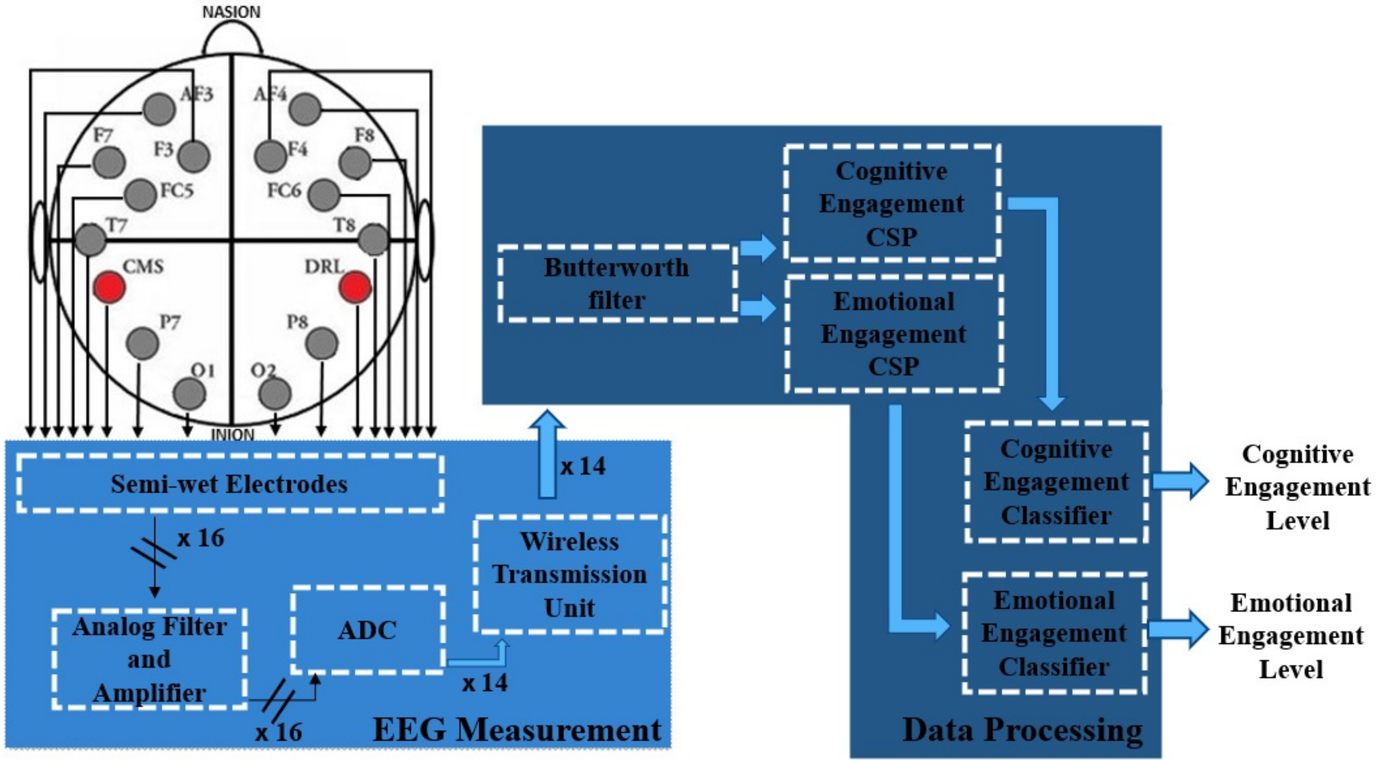


Figure 3.10: The proposed cognitive engagement detection method for rehabilitation.

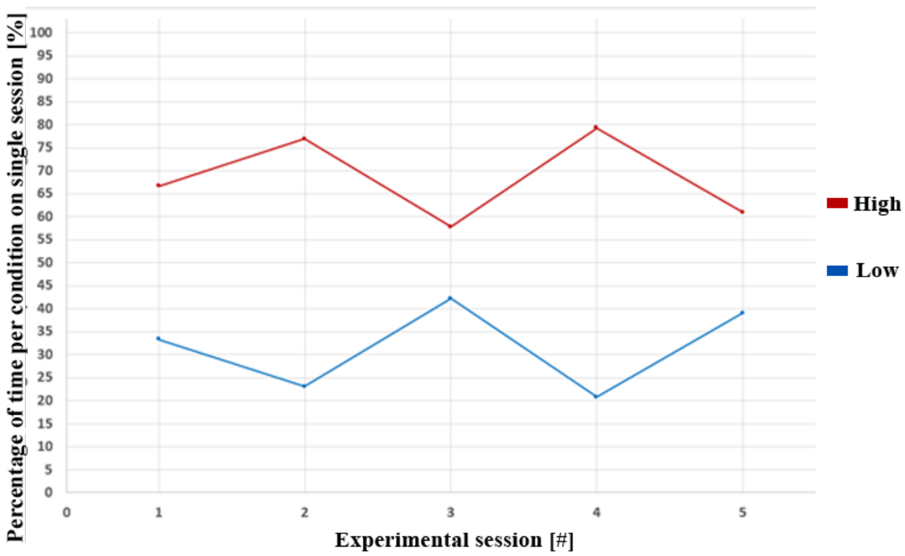


Figure 3.11: Time-trend analysis of the observed conditions during the entire therapy of cognitive engagement

These results are important steps for cognitive engagement detection and to evaluate the related cognitive load in everyday conditions. This is an important first step to be able to analyze the effect of the working memory and cognitive load during the gait analysis.

These results are a further demonstration of the possibility of an EEG-based cognitive engagement detection. The employ of a game in the rehabilitation field identifies new application contexts for this type of analysis. The conjunction of a motor act (object pursuit) and a cognitive task its similar to what happen wile walking. Therefore, being able to monitor the levels of cognitive engagement allows to provide further information on the cognitive condition of the subject during gait.

Chapter 4

EEG Features for Executive Function Identification

4.1 Overview

In the analysis of the gait, balance, and posture, the Executive Functions (EFs) play a fundamental role. During the gait, low and high level EFs are called up. Planning, inhibition, working memory, reasoning and problem solving are necessary for the subject to be able to manage any condition during the walk. The EFs are a set of neurocognitive processes involved in goal-oriented problem solving [150]. According to Miyake and al., there are three main areas of executive functions: inhibition, working memory, and cognitive flexibility [151]. Inhibition is linked to the activation of networks involving bilateral frontal, upper right temporal occipital and lower left, right thalamic structures, and midbrain [152]; working memory involves dorsolateral prefrontal cortex [153]; while flexibility relates to prefrontal and posterior parietal cortex [151]. As concerns inhibition, Barkeley identifies three different sub-processes: (i) the inhibition of the continuous response (interrupting an ongoing response no longer effective); (ii) the cognitive inhibition (i.e. the ability to suppress an initial overbearing mental representations); and (iii) the inhibition of interference or inhibitory control of attention allowing to participate selectively, concentrating on the stimuli and suppressing the attention on the other [154]. The Working memory (WM) updates and keeps in mind the information. Baddeley organizes WM in two sub-processes: (i) phonological loop (deals with the phonetic and phonological treatment ensuring the temporal properties preservation); (ii) visuo-spatial sketch-pad (maintains and processes the visual-spatial information and it has the ability to generate mental images); and (iii) episodic buffer (archive which contains episodes and it represents a bridge with long-term memory) [155]. The cognitive flexibility represents creative and adaptive mindset to rapid circumstance variations. It is the ability to switch from one set of stimuli to another according to the context of a situation [156]. The combination of two or more of these EFs gives rise to complex functions such as problem solving, planning, and reasoning [37] [38].

These EFs are invoked in the processes involving gait, posture, and balance. Planning the way, identifying the sources of danger and reasoning on alternative solutions, retrieving any previous situations in memory, are just some of the most simple methods of the using of EFs during a gait. In relation to the importance of EFs in the gait, the literature was analyzed to identify which FEs are most investigated and evaluated through the EEG. Currently, the relationship between executive functions and EEG features is not uniquely defined. Moreover many studies examine the EEG signal without clarifying which particular EF is investigated. In other studies the investigated EF is related to non-specific EEG features (i.e., already associated to other EF in the literature). For this reason, it was decided to investigate which EEG features were most employed in literature for the analysis of EFs.

Many studies analyze EFs in Attention Deficit Hyperactivity Disorder (ADHD) application. The ADHD is a neurodevelopmental disorder characterized by inattention and/or hyperactivity-impulsivity. According to the fifth edition of Diagnostic Statistical Manual of Mental Disorders (DMS-5), symptoms of inattention and/or hyperactivity-impulsivity must be present before age 12, in two or more contests, such as school and home. Impairment contributes to academic, professional, or social dysfunction. These symptoms must be present for at least 6 months and do not occur exclusively during schizophrenia or another psychotic disorder and must not be better explained by another mental disorder (mood disorder, anxiety disorder, dissociative disorder, personality disorder). The attention deficit hyperactivity disorder subjects present the same reduction in walking activity in relation to poor performance in the execution of the dual-task [52]. Thanks to collaboration with Villa delle Ginestre (neurorehabilitation center) we investigated on the ADHD children. In complex pathologies, such as in the case of children with ADHD, walking is often compromised. The studies carried out in this context confirm what has been indicated: the walking requires the use of executive functions and their impairment affects the latter [157]. For this reason it was decided to investigate which are the most used EEG features on children with ADHD. Some of the following information are available in:

Pasquale Arpaia, Loredana Cristaldi, Mirco Frosolone, Ludovia

Gargiulo, Francesca Mancino, Nicola Moccaldi, *"EEG features of executive functions employed in the diagnosis and treatment of children with ADHD: a review."*, to be submitted to Topics in cognitive science, 2021, Wiley-Blackwell.

The aim of this review is to verify if consistent EEG features are identifiable for each EF and, in this way, contribute to the development of EEG-based diagnosis and therapies of ADHD. Consequently, as far as EEG-based studies associating ADHD to EFs deficit is concerned, the Research Questions (RQs) of this review concern:

- (RQ-I) what resolution is adopted in executive function analyses among high order-, basic-, sub-, and components of sub-executive functions;
- (RQ-II) what executive functions are the most attentioned and, therefore, considered the most significant for ADHD diagnosis and treatment;
- (RQ-III) what EEG features are mainly linked to specific EFs.

4.2 Methods

For each paper included in this review, the hidden EFs are made explicit according to the tests adopted in the experimental protocol. Moreover, in case of non-specific use of the EEG features, a comparison among the accuracy and the effectiveness of the diagnosis and therapy solutions, respectively, is proposed. The more appropriate correspondence between EF and EEG features arises when the accuracy and effectiveness performances are highest. Consequently, identifying an EEG signature of the compromised executive function will allow to improve the diagnosis and therapy of ADHD. Moreover, the achieved results could be employed to verify the proposed link between ADHD and the mainly involved EFs.

4.2.1 Database searches and inclusion/exclusion criteria

101 articles are included in this review. The following query *ADHD*, AND *EEG* AND NOT *ADULT* was employed to find the keywords within the title and the abstract of the articles in three database: Pubmed, Scopus, and IEEEXplore. In compliance with the PRISMA recommendations [158]

(include the Kitchenham's guide [159]) articles were included if respected inclusion/exclusion criteria or selection criteria:

- Age of the experimental sample: 6 - 14 years;
- participants condition during EEG signal recording: studies focused on resting state were excluded. Indeed, EFs selective activation requires specific task execution;
- comorbidities: the concurrent presence of other pathologies in participants was reason for exclusion;
- drug treatment: drug assumption must be interrupted at least six months before the execution of the experimental sessions.

As far as pharmacological treatment is concerned, if this information was not specified the articles were excluded. Finally, journal and conference articles were included, review, commentaries, and editorials were excluded.

474 articles were excluded basing on these criteria. In the eligibility phase, the full text of the remaining 393 articles was analysed. The adherence of all the articles was verified according to the criteria above indicated. After the text reading, 101 articles were included: 86 from Scopus, and 15 article from PubMed. A flow diagram representation of the database search above desctribed is showed in Fig. 4.1 and carried out in compliance with the PRISMA recommendations [158].

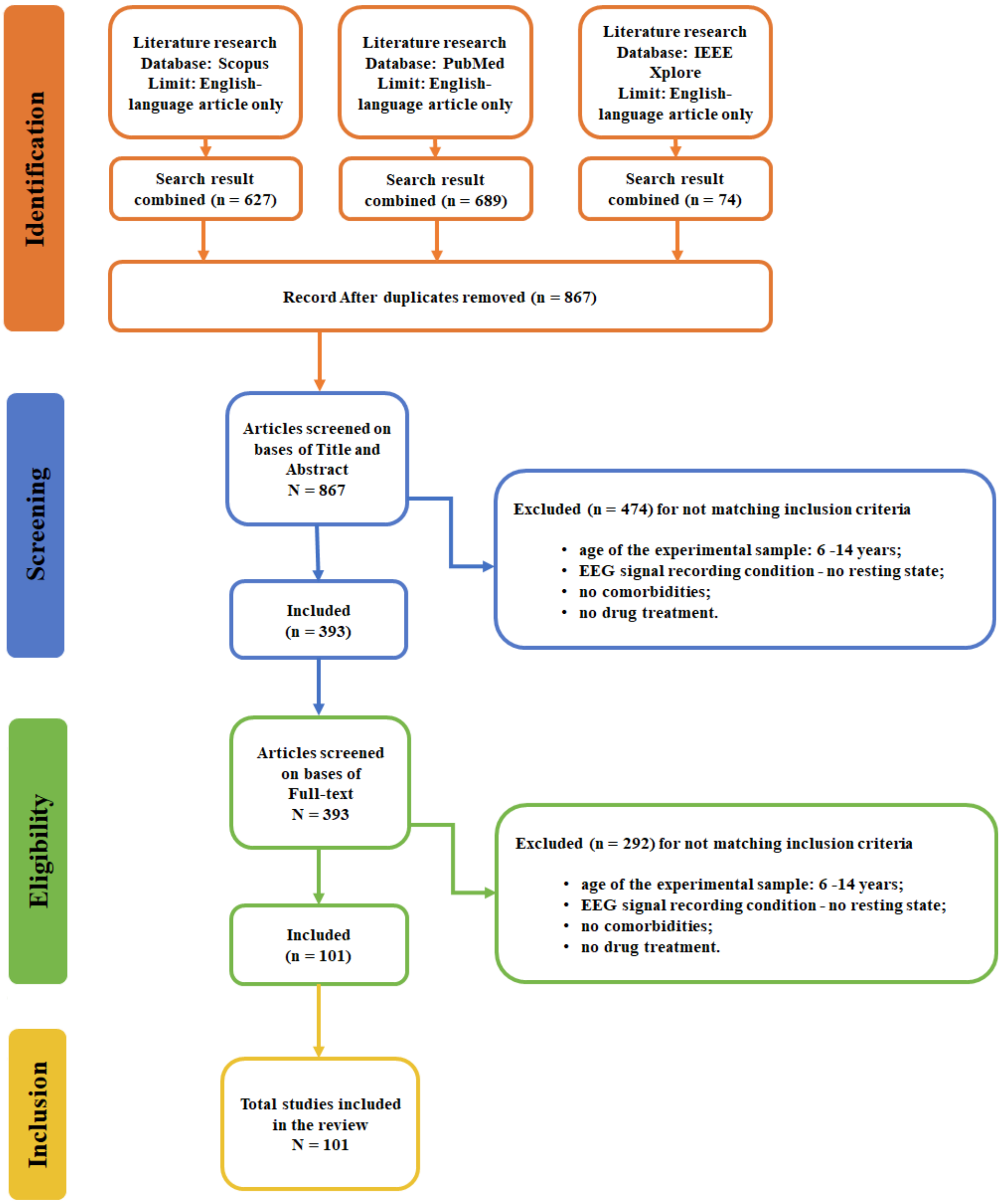


Figure 4.1: PRISMA-flow of the articles selection process.

Each article was labelled by the main executive functions focused. When the authors did not specify the EFs being investigated, the links between the EFs and the articles were based on the experimental test performed. Specific tests are administered to the subjects in order to evaluate the affected EF.

Nevertheless, an exclusive link between a test and an executive function cannot be guaranteed [160, 161]. Links among EFs and some of the main used tests are shown in Table 4.1. The proposed method to identify links among EFs and articles is articulated in mutually-exclusive successive steps as follows: (i) standard tests are implemented, therefore, articles are labelled based on the test-related executive functions; (ii) the article employed custom tests but the authors clarified the investigated EFs,therefore, articles are labelled based on the declared EFs; (iii) custom tests are used and the authors did not declare to focus on specific executive functions, therefore, articles are labelled based on EFs related to the most similar standard test.

Table 4.1: The table shows the FE investigated mainly in children with ADHD and the main tests that allow their analysis

Basic Executive Function	**Sub-Executive Function**	**Main Related Test**
Inhibition	Response Inhibition	Go/No Go Task [162]
	Interference Inhibition	Flanker Test [163]
Working Memory	Verbal Working Memory	N-Back Task [164]
	Visual Spatial Working Memory	Corsi Block Test [165]
Cognitive Flexibility	-	Wisconsin Card Sorting Task [166]

4.2.2 EEG features identification

In the case of therapeutic articles, two features are often proposed, one for treatment and the other for testing the effectiveness of the treatment. In these cases, the EEG feature proposed for the treatment is considered. All the features collected from the articles are organized according to a multi-level schema (Fig. 4.2). The first level is the domain of definition: spatio-temporal, spatio-frequency or spatio-time-frequency domain. In all cases it is possible to consider the spatial domain given the distributed mode of recording the EEG signal: it is acquired in certain region of the scalp depending on the chosen headset. At this level the signal is treated by referring to peculiar pre-processing (averaging) or transformation (Fourier, Welch,...). As far as the second level is concerned, the sub-domain are adopted; namely, the temporal sub-domains and the bands (alpha, beta, theta,...). Finally, in third level, the features identification is completed by means to a synthetic value extracted after a specific operation (mean, amplitude, power spectral density, . . .).

In order to find the EEG features linked to the compromise of an executive function, the number of studies considering a certain EEG feature is plotted for each most investigated executive function. In the first analysis, the number of articles linking inhibition and working memory (and related sub-functions) to EEG features defined in the spatio-temporal, spatio-frequency,

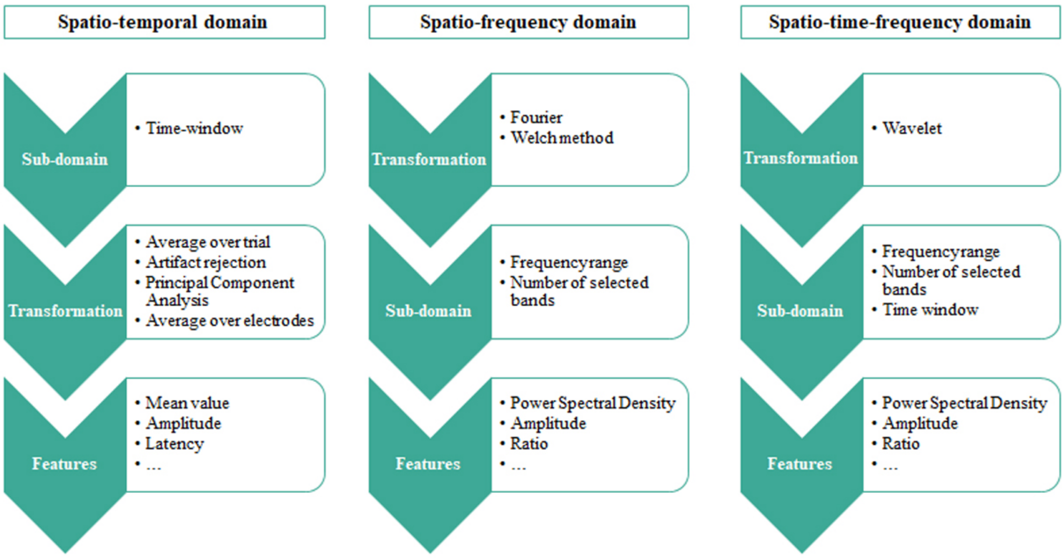
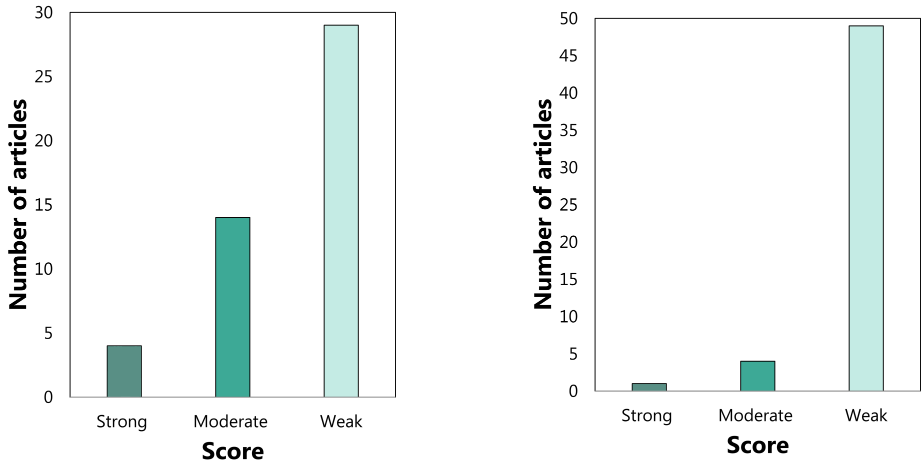


Figure 4.2: EEG features classification scheme.

or spatio-time-frequency domain was assessed. Then, separately for each domain, the specific EEG features is considered: the number of articles, centred on a particular EF, is plotted as a function of the EEG features.

4.2.3 Quality assessment strategy

The Quality Assessment Tool for Quantitative Studies (QATQS), created by researchers from Canada's Efficient Public Health Practice Project (EPHPP) was used for the quantitative assessment of the quality of the reviews, as suggested by the PRISMA guidelines [167] [168].
All the included studies were statistically classified according to the six components of QATQS: (1) selection bias, (2) study design, (3) confounders, (4) blinding, (5) data collection methods, and (6) withdrawal and dropouts. The quality of each of the six components was assessed by assigning a score from 1 to 3. If the analyzed paper reflects all the characteristic points of the section, the score assigned to it is *one (strong)*. If the paper partially reflects these characteristic points, the score is *two (moderate)*. If no point is met, the score assigned is *three (weak)*. The analysis results show 5 strong, 18 moderate and 78 weak. In particular, 4 strong, 14 moderate and 29 weak diagnostic articles have emerged from the application of the above criteria, as shown in Fig. 4.3 a). Regarding the therapeutic articles, 1 strong, 4 moderate and 49 weak articles have arisen, as shown in Fig. 4.3 b). Regarding thera-



(a) diagnostic articles

(b) therapeutic articles

Figure 4.3: Global Rating of: a) diagnostic, and b) therapeutic articles

peutic articles, 72 % of authors chose a control group, 9 % of authors have performed a double-blinded study, 85 % of authors preferred to administer evaluative questionnaires rather than the acquisition of further biomedical signals and 9 % of authors argued the exclusion criteria in detail. Regarding diagnostic articles, 92 % of authors considered a control group, 21 % of authors have evaluated further biomedical signals and have administrated evaluative questionnaires and 23 % of authors argued the exclusion criteria in detail.

4.3 Results

The articles review results suggest that 96 % of the articles analysed executive function without distinction between sub-function, the 71 % considered separately the sub-components of inhibition and working memory while 4 % dwelled on high-order EFs (i.e. reasoning, planning and problem solving), resulting from the simultaneous action of two or more Executive functions [36]. The most investigated executive functions are inhibition and working memory: the 64 % of the articles investigate the inhibition and its sub-function and the 30% the working memory and its sub-function (Fig. 4.4. In particular, as concerns sub-function, 26 articles focus on response inhibition, 47 on interference inhibition. Regarding working memory, visuo-spatial working memory is investigated by 17 articles, verbal by 3 studies (Fig. 4.5). The interference inhibition and visual-spatial working memory are the mainly studied sub-functions (51 % and 17 %, respectively compared to all inhibition and WM sub-functions).

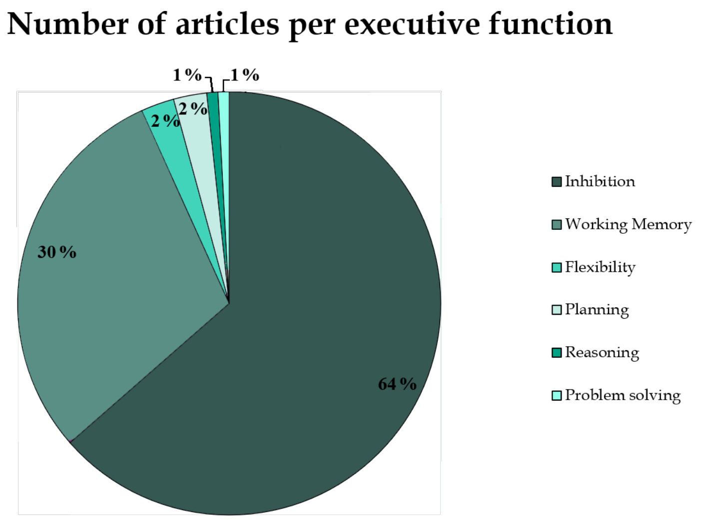


Figure 4.4: Percentage of Executive Function considering respect to all EFs evaluated

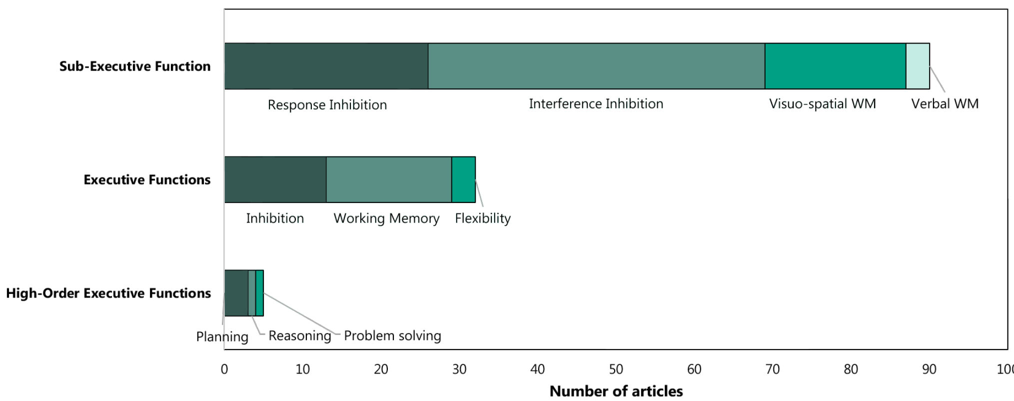


Figure 4.5: Number of articles per Executive Function considering the level of details in analysis of Executive Functions

Considering the definition domain of features: the features related to the inhibition are evaluated at 52 % in the temporal, at 45 % in the frequency domain, and at 2 % in the tempo-frequency domain. The WM-related features are evaluated at 28 % in the temporal, at 71 % in the frequency domain, and 1 % in the tempo-frequency domain. About the results of inhibition, the domain of analysis of the EEG signal are both the temporal and frequency domain. Regarding working memory, EEG features are analyzed predominantly in the frequency domains. In particular, for ADHD diagnosis or treatment based on impaired inhibition, 44 studies consider temporal features, 39 frequency features while 6 articles analyse tempo-frequency features. Concerning diagnosis during working memory tasks, most of the studies focus on the features defined in the temporal and frequency domains (13 and 21 articles, respectively) and only 2 articles consider EEG features defined in the tempo-frequency domain. In the case of inhibition, there is a slight trend in considering the amplitude of the P300 and N100 components of the Event related Potentials (ERPs) and the power spectral density in the α, and θ band. In particular, several authors conclude that there is a difference between ADHD subjects and control in P3 and N1 amplitudes during inhibition tasks (Fig. 4.6).

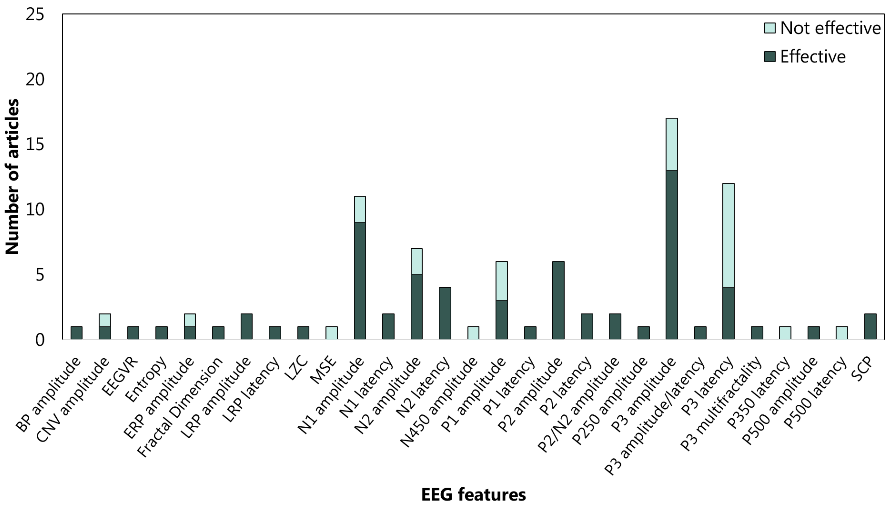


Figure 4.6: EEG features for inhibition in time domain. LZC: Lempel-Ziv Complexity; EEGVR: Electroencephalogram Valid Rate. MSE: Multi-Scale Entropy. SCP: Slow Cortical potentials

Other studies identify an higher α, and θ activity in the ADHD groups compared with controls during inhibition tasks (Fig. 4.7).

Regarding WM, a trend emerges in frequency domain linking working memory to power spectral density in α, β, and θ bands (Fig. 4.8. In the time domain, as described above, WM is not much evaluated, and there is no detectable prevalence of features (Fig. 4.9).

Concerning inhibition sub-function, the interference inhibition is not very

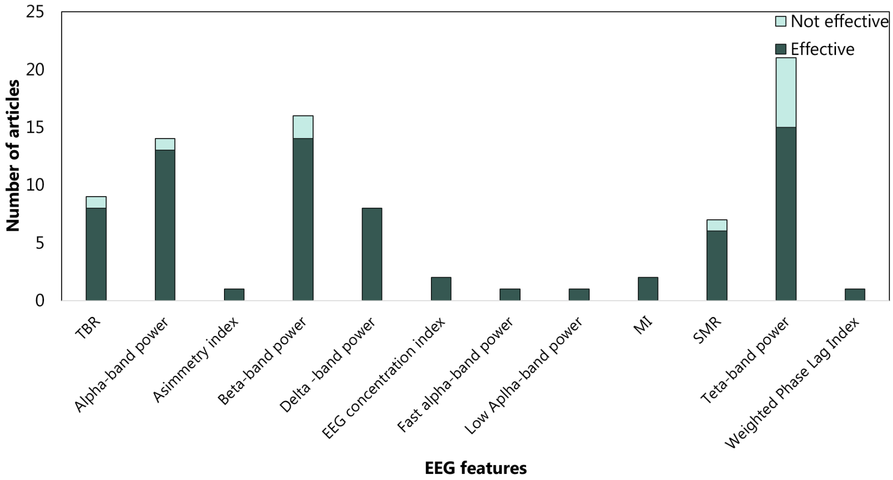


Figure 4.7: EEG features for inhibition in frequency domain. MI: Modulation Index. SMR: Senso-motor rhythm.

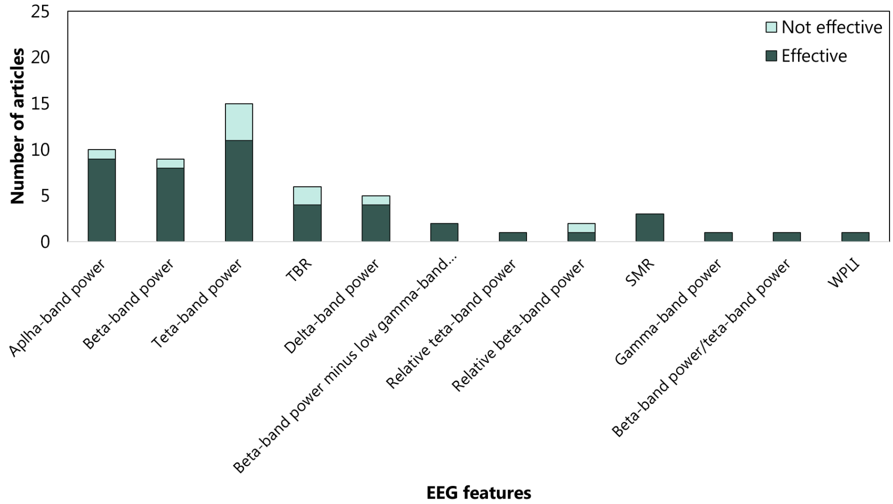


Figure 4.8: EEG features for working memory in frequency domain.

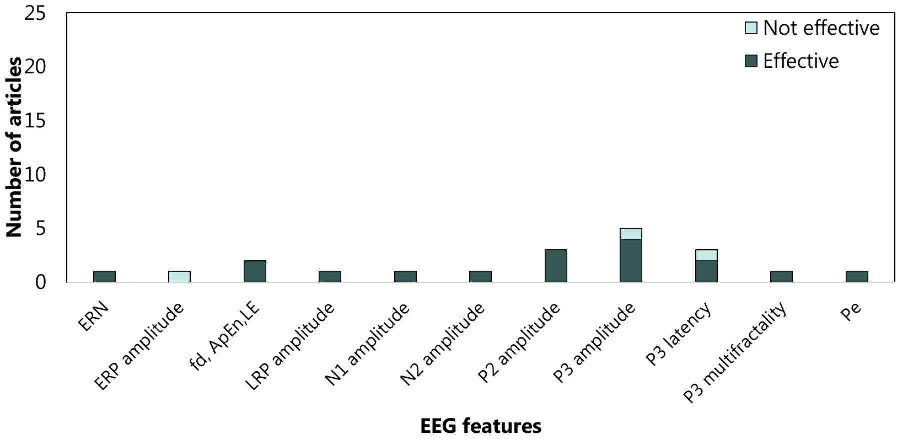


Figure 4.9: EEG features for working memory in time domain. TBR: Theta Beta Ratio. SMR: Sensorimotor rhythm. WPLI: Weighted Phase Lag Index

studied in the time-domain (Fig. 4.10), but a slight link emerges between interference inhibition and spectral density in α, β, and θ bands in frequency domain (Fig. 4.11).

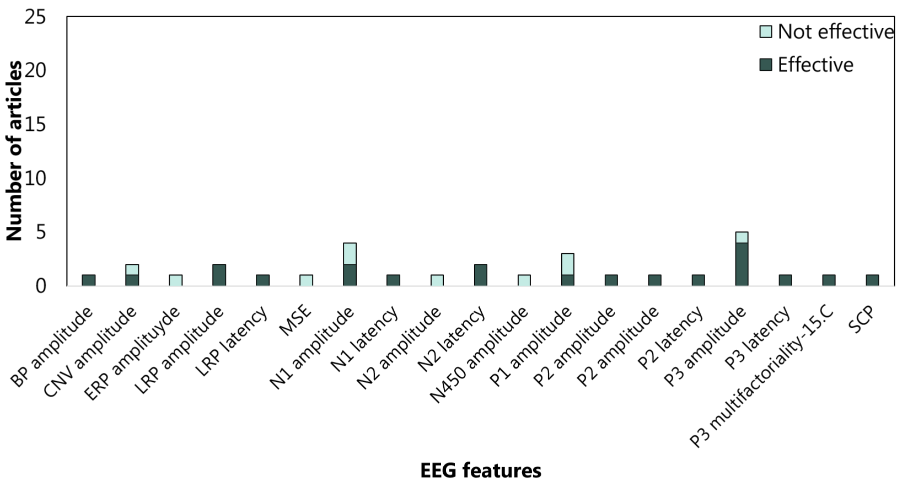


Figure 4.10: EEG features for interference inhibition in time domain.

For the WM sub-functions, the visuo-spatial working memory are the only one evaluated. The must investigate sub-domain are again the α, β, and θ bands.

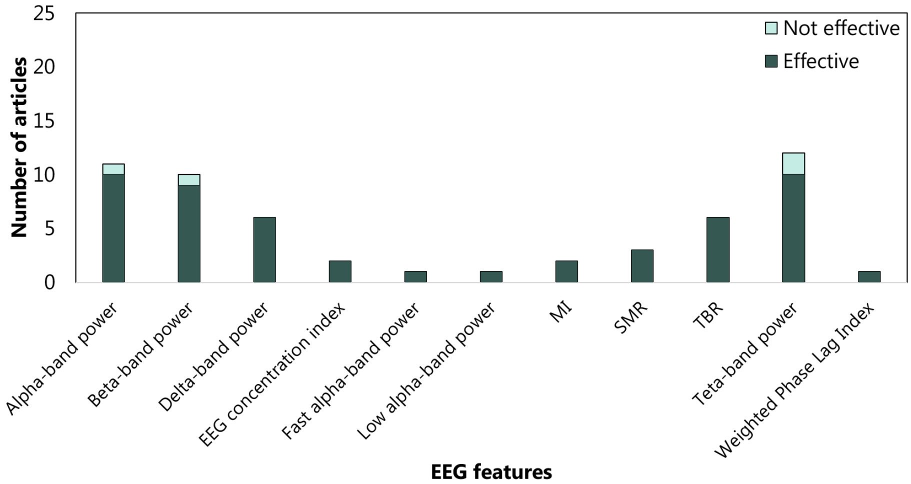


Figure 4.11: EEG features for interference inhibition in frequency domain. TBR: Theta Beta Ratio; MI: Modulation Index; CI: EEG Consistency Index;

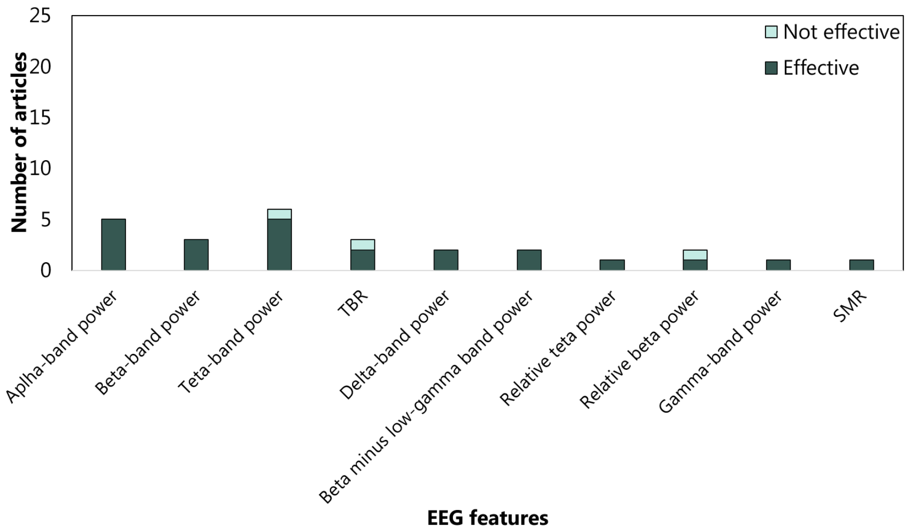
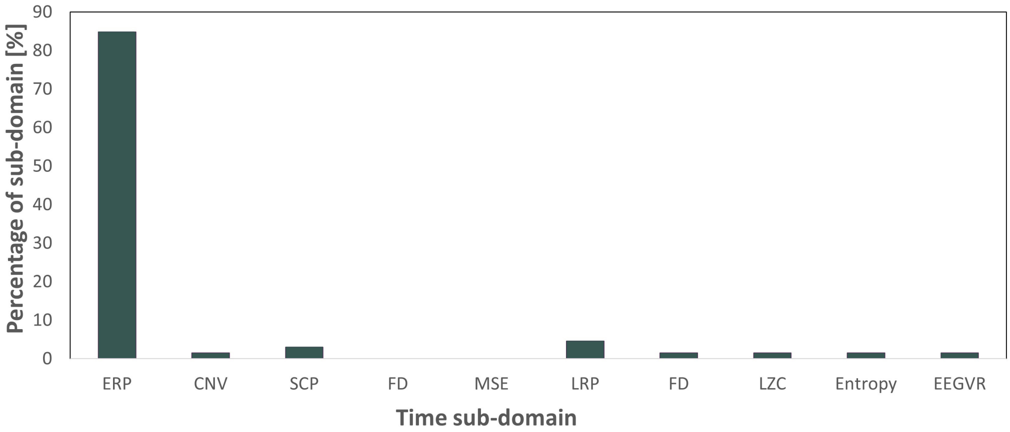


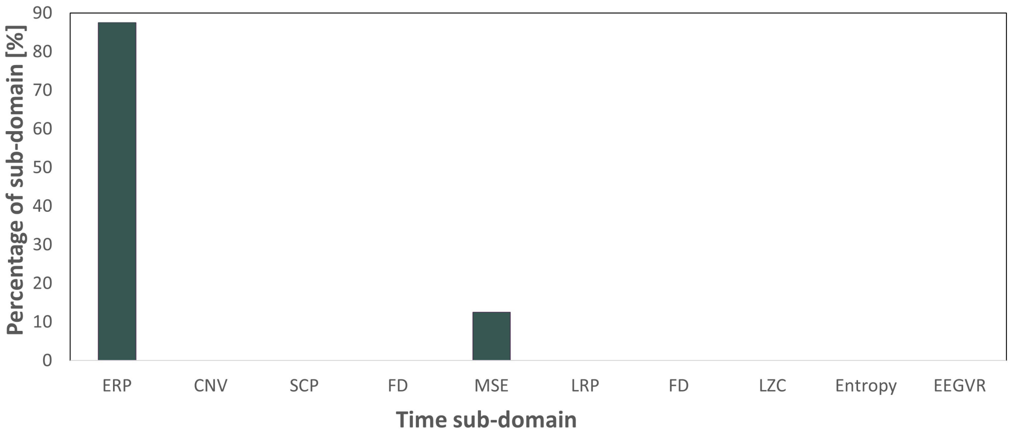
Figure 4.12: EEG features for visuo-spatial working memory in frequency domain.

As regards the sub-domain, the most employed is the ERP in time sub-domain and the θ, β, and α (in descending order) in frequency domain. In particular for the time sub-domain:

- about 85 % of articles consider features in the ERP sub-domain for inhibition and its sub-function interference inhibition (Fig. 4.13 a and Fig. 4.14 a);

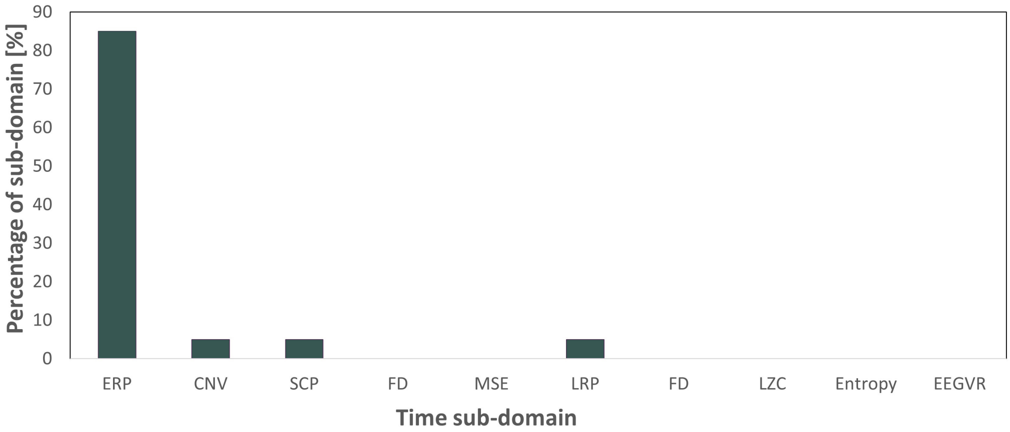


(a) Inhibition sub-domain percentage

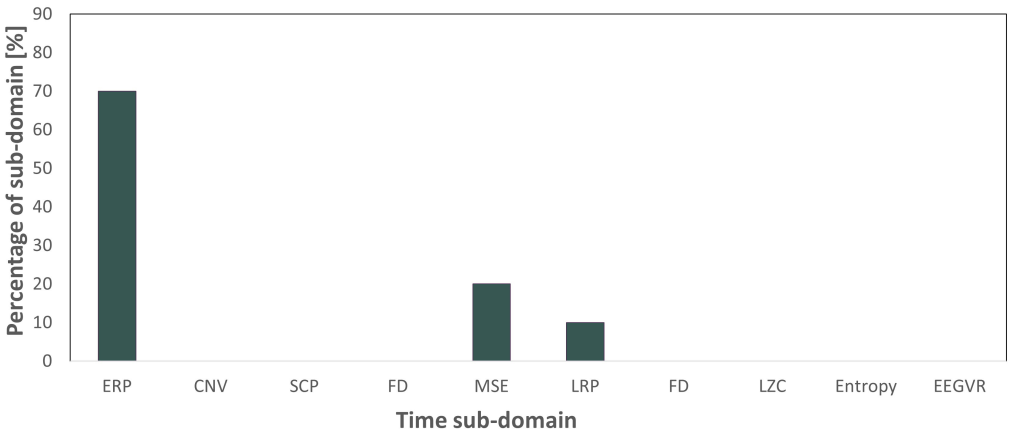


(b) Working Memory sub-domain percentage

Figure 4.13: Percentage of number of articles employing features in sub-domain respect to the time-domain for the: a) inhibition, and b) Working Memory.



(a) Interference inhibition sub-domain percentage



(b) visuo-spatial working memory sub-domain percentage

Figure 4.14: Percentage of number of articles employing features in sub-domain respect to the time-domain for the: a) interference inhibition, and b) visuo-spatial Working Memory.

- about 88 % of articles consider features in the ERP sub-domain for WM (Fig. 4.13 b) and 70 % for the visuo-spatial working memory (Fig. 4.14 b).

For the frequency domain, instead:

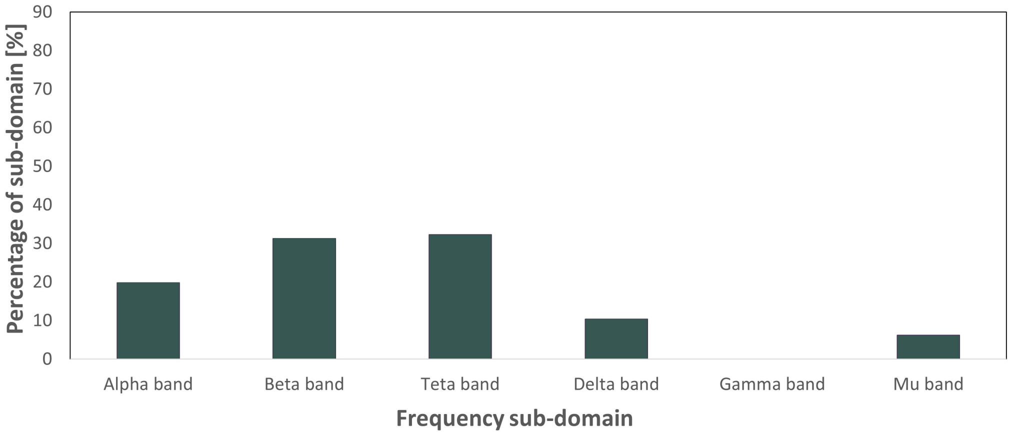
- about 30 % of articles consider features in the θ, and β and 20 % in the α sub-domain for the inhibition and its sub-function interference inhibition (Fig. 4.15 a and Fig. 4.16 a);
- about the same percentage of articles consider features in the θ, and β for the WM (Fig. 4.15 b) and the visuo-spatial working memory (Fig. 4.16 b).

For the visuo-spatial WM, an important consideration involves the employ of the γ sub-domain usually not used for the others EFs (Fig. 4.16 b).

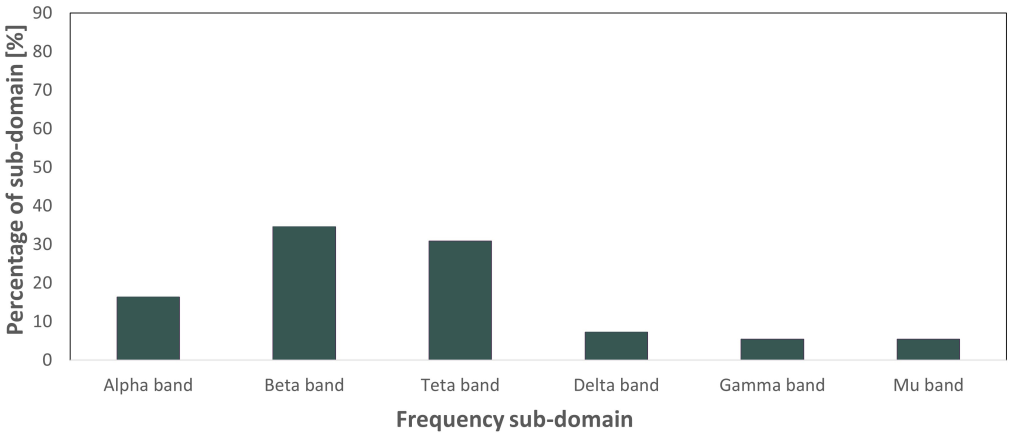
Finally, about the most evaluated features with respect to all features in the same domain, the results show:

- P300 amplitude is the most widely used feature in time domain. About 20 % of articles employed P300 amplitude for the evaluation of inhibition, working memory, and their sub-functions (interference inhibition, visuo-spatial WM);
- in the frequency domain, the θ-, α-, and β-band power are the most employed features. About 20 % of articles employed θ-, α-, and β-band power, for the analysis of inhibition, WM and their sub-functions.

Starting from this analysis, the study of EFs must be thoroughly investigated (especially employng the EEG system). The EEG features most exploit in this area do not use recognition systems based on machine learning and artificial intelligence but different data processing method. The most employed EEG features are not uniquely linked to the elicited EF but rather to the literary indication or to the tools and instrumentation available. The investigation becomes more complex if we talk about the analysis of all the EFs involved during gait, posture, and balance. However, the knowledge of how the literature investigates these phenomena is essential to recognize a method of analysis of the gait. The confirmed employing of the EEG-features in the frequency domain for all literature-investigated EFs, is an important result to furthers ideas to: study the EFS and prevent the risk of fall during walking.

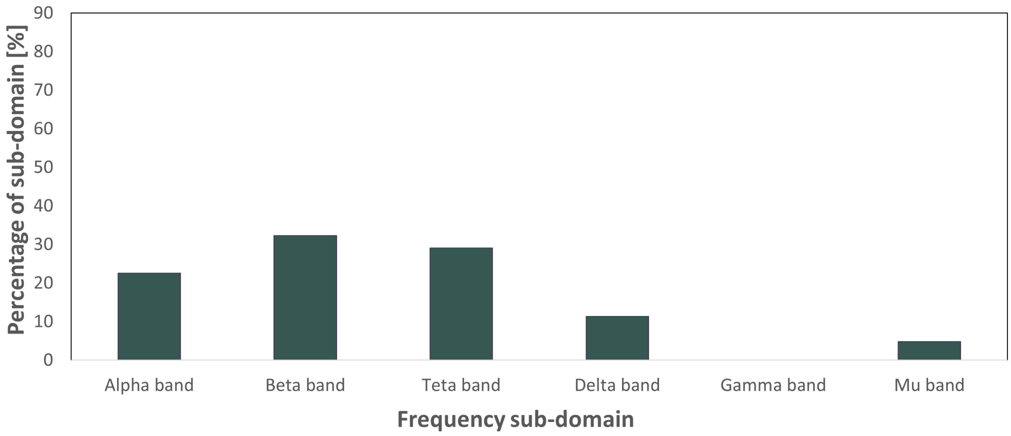


(a) Inhibition sub-domain percentage

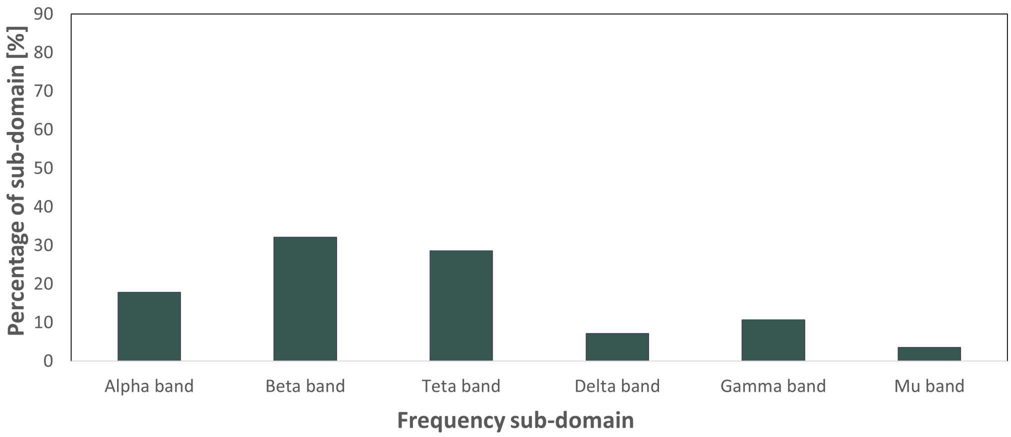


(b) Working Memory sub-domain percentage

Figure 4.15: Percentage of number of articles employing features in sub-domain respect to the frequency-domain for the: a) inhibition, and b) Working Memory.



(a) Interference inhibition sub-domain percentage



(b) visuo-spatial working memory sub-domain percentage

Figure 4.16: Percentage of number of articles employing features in sub-domain respect to the frequency-domain for the: a) interference inhibition, and b) visuo-spatial Working Memory.

Chapter 5

Attention Detection during Dual-task Execution

In this chapter, an EEG-based method for attention assessing during the execution of a dual-task has evaluated. A study on the distraction detection during the execution of a rehabilitation task was carried out. Motor act distraction was assessed by applying an oddball paradigm. The reported study shows the possibility of exploiting a wearable and non-invasive EEG system to discriminate attention to the motor act performed by the subject. The possibility of obtaining information on attention during a dual-task execution is a fundamental element in gait analysis and especially in relation to the risk of fall.

5.1 Overview

Among the cognitive processes contributing to falls, attention certainly plays a fundamental role. Walking while performing one or more different tasks depletes cognitive resources. The attention is focused on one task while neglecting another. When the subjects are affected by pathology, this condition becomes even more critical; the result of the action of multiple concurrent tasks increases the risk of falls for the subject. The attention is a highly studied construct in the literature in various different context. In the last studies, the attention is increasingly considered a specific example of EF [169]. Ladvas and Berti describe attention as the function that regulates the filtering and organization of the information received from a subject, allowing his/hers adequate responses [170]. Sohlberg and Mateer propose a characterization of attention in four different dimensions [171]:

i the *Arousal* indicates the activation level and defines the psychophysiological activation allowing the afferent of the different stimulation;

ii the *Selective attention*: points out the ability to focus attention on a specific source or sensory channel;

iii the *Distributed attention* is the ability to simultaneously process information from multiple sources;

iv the *Sustained attention* is the ability to direct and maintain cognitive prolonged activity on a specific stimuli.

In everyday life, many types of distracting effects (visual, auditory, and their combinations) sidetrack attention when performing any task, especially if it requires engagement [172]. Diez et al. identified attention just as the ability to select interesting stimuli, by ignoring other distracting stimuli in the surrounding environment [173]. These distractors play a fundamental role in analyzing the attentional process [174]. Changes in cognitive processes related to attention activate different parts of the brain. Concurrent distracting events deactivate certain brain areas by activating other ones [175]. In recent years, many studies have highlighted the concept that: gait/walking requires attention [176, 177]. As already described above (1.2), the best method for analyzing this link is dual-tasking. By "dual tasking" we mean the simultaneous execution of an active movement (motor skills) and a mental task (cognition); for example walking and talking at the same time, or go up the stairs (motor skills) and recognize the house key in the set of keys (cognition). A very useful context for identifying the mechanisms underlying attentional processes is an analysis of a motor gesture in the presence of a double task during rehabilitation therapy. Therefore, a distraction detection EEG-based system during a motor rehabilitation exercise are evaluated. The knowledge of the most promising EEG features represents the starting point for the preparation of a more complex study to be carried out in the field of walking and gait.

Some of the following information are available in:

Andrea Apicella, Pasquale Arpaia, Mirco Frosolone, Nicola Moccaldi, *"High-wearable EEG-Based Distraction Detection in Motor Rehabilitation."*, Scientific Reports, 2020, 11(1), 1-9. Nature.com. doi:10.1038/s41598-021-84447-8.

5.2 Key concepts

Ang et al. prove that a neuromotor rehabilitation exercise induces neuronal neuroplasticity and promotes motor recovery [178]. In particular, the repetition of the exercise induces a reorganization of the motor cortex. However, the repetition of the same exercise may induce weariness in the subject and prevent a careful focus on the performance of the exercise. Conversely, completing the exercise, while maintaining the attention focus in a sustained and selective way, promotes neuronal plasticity and motor learning [179, 180]. The attention to the motor task has an enhanced effect on rehabilitation performance[136]. Many studies deal with assessing the attention and its different dimensions through the analysis of the brain signals using the EEG [181]. Several studies have shown that the level of attention affects the EEG signal [182, 183]. Therefore, variations in the EEG signal can be used to detect corresponding changes in attention levels [184]. Attention creates a variation in brain signals that can be assessed both in the time and in the frequency domain [185]. In this study a method for detecting distraction during motor rehabilitation is proposed. The method is based on the following key concepts:

- *EEG-based distraction detection*: During a rehabilitation motor task, EEG trend is influenced by the state of the patient attention or distraction to the task itself.

- *Attention vs distraction definition*: Focusing on motor task means imagining, with open eyes, the movement while its execution and trying not to think about anything else. A distracting condition occurs when the patient performs an entirely absorbing cognitive task while continuing to carry out the rehabilitation movement. To the end of evaluating the phenomenon, a rehabilitative motor task is carried out. The assignment is run under conditions of concentration on the action and in the presence of a distractor (auditory, visual, and visuo-auditory) which engages the learner in a concurrent cognitive task analogously as what done in Asayb et al [186].

- *Metrology perspective*: An applied metrological and instrumentation-aimed approach is guaranteed, for the first time, in the EEG based distraction detection.

- *Feature extraction enhancement*: A multiple bandpass Filter-Bank, in combination with a Common Spatial Pattern algorithm, selects spatial, temporal and frequency features. In particular, a 12-band Filter-Bank is proposed for enhancing, the peculiar contribution of the delta, theta, and alpha bands as fundamental in the analysis of attentional processes [187], compared to previous 9-band approaches [85].

- *High Wearability*: The EEG acquisition system is realized in ultra-light foam. The ergonomic and comfortable device is equipped with a rechargeable battery and transmits the acquired data via Bluetooth. Dry electrodes avoid the inconvenient of electrolytic gel.
- *Clinical applicability*: wearability cannot be a prejudice for accuracies compatible with clinical use. A method with state-of-the-art accuracy (greater than 80 % [186, 85]) is required.
- *Validation based on wide comparison*: Performance of the proposed method are compared with different strategy of EEG feature extraction (including the proposal of Hamadicharef et al. [85]), and different types of classifiers.

5.3 Experimental design

A session was based on seventeen volunteers subjects (eleven males and six females, with an average age of 30.76±8.15). A written informed consent was obtained from each volunteer before the experiment. All experiments were carried out in accordance with relevant guidelines and regulations. The ethical committee approved the experimental protocol of the University of Naples Federico II. All of them had a normal clinical history with normal vision and normal hearing, and no neurological disease. The participants were seated in a comfortable chair with armrests, in a very quiet room, about one meter away from a PC screen. After wearing the EEG-cap, participants were requested to execute a squeeze-ball exercise whenever a start command appeared on the PC screen. Squeeze-ball is one of the most common hand rehabilitation exercises [188]. Following a period of immobilization in plaster, after a surgical intervention or in the presence of inflammatory or degenerative pathologies (e.g., arthrosis, rheumatoid arthritis), hand-ball rehabilitation showed to be important in maintaining or restoring the functional use of the hand [189]. Motor task execution consists of maintaining attention focused only on: (i) the squeeze movement (*attentive-subject trial*), or (ii) a concurrent distractor task (*distracted-subject trial*); in both trials the participant must perform the squeeze-ball movement. Attention to motor task execution was supported by employing an aneroid sphygmomanometers: volunteers were asked to focus the aneroid gauge, while squeezing the bulb and pumping air into the cuff. The distractor task was based on the *Oddball paradigm* [190, 191]: the presentations of sequences of repetitive stimuli, infrequently interrupted by a deviant stimulus. The oddball paradigm is one of the most widely used methods to study the neurophysiology of attention. In the proposed protocol, the volunteer was asked to count the number of certain stimuli sequences. Three types of stimuli sequences were proposed: (i) acoustic, played with a conventional headphone, (ii) visual, displayed on a PC screen, and (iii) and visual-acoustic combination [192]. Each participant completed one session composed of 30 trials: 15 *attentive-subject trial* and 15 *distracted-subject trial*. The trials sequences were randomly chosen for minimizing the influence of task learning. Each trial consisted of: 2 s task presentation, 9.5 s task execution and 5 s relax. Furthermore, a 15 s baseline was acquired at the beginning of the session. In the following, trial contents are detailed:

- *Attentive-subject trial*
  An Attentive-subject trial notification appears for 2 s on the PC screen. Then, a ball-squeezing image triggers the start of the motor exercise and a new message on the screen asks the subject to focus on the squeezing movement. At the end of the task execution, an image of a relaxing landscape is is shown for 5 s.

- *Distracted-subject trial*
  A notification concerning the distractor task (Audio, Visual or Audio-Visual) appears for 2 s on the PC screen. Then, an acoustic message notices the beginning of the motor exercise; a distractor task (based on Oddball paradigm), chosen among the followings, starts:

  - The *Audio Distractor* is based on the auditory oddball paradigm. Eight tones sequences sound through the earbuds. Tones range among three different frequencies: *low*, 500 Hz, *middle*, 1200 Hz, and *high*, 1900 Hz. The tone *low* has 50% probability of occurrence. The occurrence probability of the *middle* and the *high* tones is 25%. The target sequence is the appearance of a diverted tone after the other more frequent one: when the *middle* tone occurs immediately after the *low*, or when the *high* occurs immediately after the *low*. Others combinations are not considered as target occurrences.
  - The *Visual Distractor* task is based on the visual oddball paradigm. Three 2D-Gabor masks were used with different orientation: 90, 60, and 30° (Fig. 5.1). The 2D-Gabor mask is a Gaussian kernel function modulated with sinusoidal plane wave.

The most probable Gabor (50% of probability) has orientation of

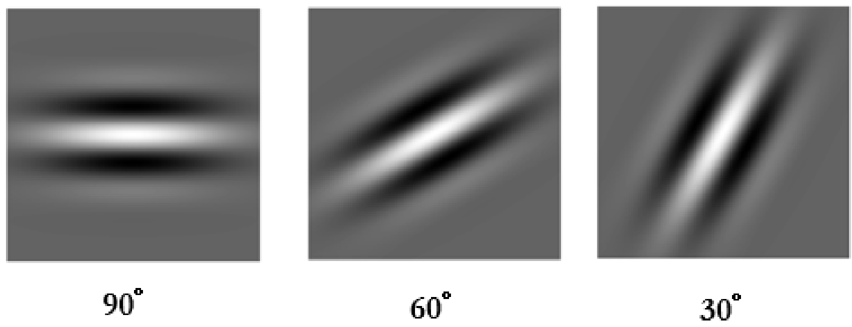


Figure 5.1: Visual Distractor task elements based on visual Gabor mask with different orientation: 90°, 60°, and 30°.

90° , while the diverted Gabor (25% of probability) has 60 or 30° orientation. Eight Gabor sequences occurred on the PC screen. The target sequence was the occurrence of diverted Gabor mask (with orientation of 60 or 30°) after the most frequently with 90° orientation.

– The *Audio-Visual Distractor* task is a combination of the previous oddball paradigms. Eight between tone and Gabor sequences occur randomly. The target sequence is the occurrence of any Gabor mask after the tone. Others combination sequences are not target occurrences.

At the end of the task, a relaxing landscape is presented for 5 s. During the relax period, the subjects are asked to give the number of the observed targets.

The EEG signal was acquired using a Helmate8 of *AB-Medica Helmate* [80] (Fig. 5.2 A) (for more information see 2).

5.4 Data processing

During the experiments 4590 epochs composed of 8 channels of 512 samples were acquired. In Table 5.1 number of (i) subjects, (ii) sessions, (iii) trials, (iv) epochs per trial (v) epochs per subject, and (vi) epochs as a whole are reported.

Half of the epochs were collected during the *attentive-subject trials* and were labeled as belonging to the first class. The remaining part was acquired during the *distracted-subject trials* and was labeled as belonging to

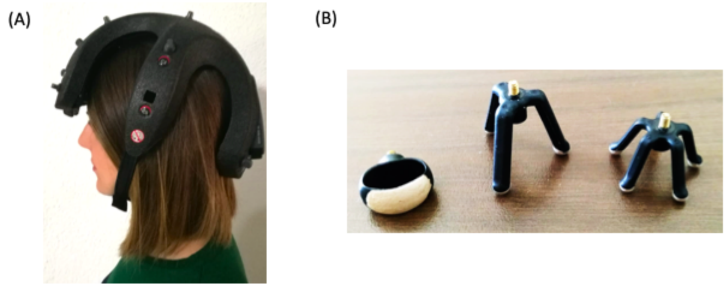


Figure 5.2: (A) EEG data acquisition system *Helmate8*, and (B) Different configuration of dry electrodes from *abmedica*. [80].

Table 5.1: Data-set composition

Subjects	Sessions	Trials per Session	Epochs per trial	Epochs per subject	Total Epochs
17	3	30	3	270	4590

the second class. The recorded EEG was divided in 3 s epochs. Each epoch was filtered between 0.5 and 48.5 Hz using a zero-phase 4th-order digital butterworth filter. An independent component analysis (ICA) algorithms - Infomax-ICA[193] - was used for artifact removal. In particular the version implemented by *Runica* module of *EEGlab* tool was adopted. Feature extraction was implemented either in time domain and frequency domain. For the latter Relative and Absolute Power Spectral Density at varying of frequency bands were considered. Three different frequency bands articulation were examined:

i) seven traditional EEG bands: delta [1–4] Hz, theta [4–8] Hz, alpha [8–12] Hz, low beta [12–18] Hz, high beta [18–25] Hz, low gamma [25–35] Hz, and high gamma [35–45] Hz; in this case, the number of features for each epoch was 112 (7 bands * 2 PSD (relative and absolute) * 8 channels);

ii) nine 8 Hz bands, 4 Hz overlapped, in the range [1-40] Hz; the number of features for each epoch was 144 (9 bands * 2 PSD (relative and absolute) * 8 channels);

iii) twelve 4 Hz bands, non-overlapped, in the range [0.5-48.5] Hz; the number of features for each epoch was 192 (12 bands * 2 PSD (relative and absolute) * 8 channels);

Regarding time domain, the feature extraction was based on four different approaches:

1) only CSP: in this case, the number of features for each epoch was 8 (CSP remaps the input information in a new space with dimensionality equal to the number of channels);

2) CSP preceded by different types of Filter-Banks: three different types of Filter-Banks were applied with the same band articulation proposed for the feature extraction in the frequency domain. In these cases CSP remaps the input information in a new space having dimensionality equal to the number of channels (8) multiplied with number of bands, obtaining 56, 72, and 96 number of features respectively.

CSP is one of the most employed feature extraction methods for classifying EEG signals [85, 86]. In a binary problem, the CSP acts by calculating the covariance matrices relating to the two classes. These two matrices are simultaneously diagonalized in a way that the eigenvalues of two covariance matrices sum up to 1. Through the subsequent use of a bleaching matrix, a suitable projection matrix is identified in order to reorganize the input into a number of components consistent with the dimensions of the input matrix. In a binary problem, these components are sorted on the basis of variance in order: (i) *decreasing*, if the projection matrix is applied to inputs belonging to class 1, and (ii) *ascending*, in case of inputs belonging to class 2 [87]. Five supervised machine learning binary classifiers were used for discriminating between attention or distraction conditions: k-Nearest Neighbour (k-NN), Support Vector Machine (SVM) [128], Artificial Neural Network (ANN) [128], Linear Discriminant Analysis (LDA) [194], and Naive Bayes (NB) [195]. Regularization terms were exploited in the training procedures for neural networks and SVM learning processes, using a weight decay and the soft-margin formulation, respectively. All the classifiers were tested on the seven features types described above. For each subject, the hyperparameters of each classifier were selected by a random search with Nested Cross Validation to mitigate possible bias induced by the low sample size [196]. Differently from the classical k-fold cross validation, Nested CV is composed of two nested k-fold cross validation procedures: the inner one finds the best model hyperparameters, and the outer one estimates the performance of the inner search. Namely, in the classic k-fold CV, given a combination of the hyperparameters values, a set of data is divided into a partition of k subsets (folds). Thus, a set T_I composed of $k-1$ folds is used to train the model and the remaining fold E_I is used for the performance evaluation by computing the appropriate metric scores (e.g., accuracy). This process is repeated for all the combinations of the k folds, by making different pairs of training set T_I and test set E_I at each iteration. In this way, final average metrics scores between all the different test sets E_I are computed. This process is then repeated for each hyperparameters combination, finally returning the best average metrics values together with the related hyperparameters. In this process, the model is evaluated together with the hyperparameters tuning. Instead, in the nested cross validation CV procedure, an outer CV makes a first division of the data into l folds; then, a set T_O composed of $l-1$ folds is used as input to a classical inner k-fold CV procedure, as above described (and therefore further divided into k folds by the inner CV procedure). Then, the returned best hyperparameters values are used to train the model on the T_O set as a whole and tested on the remaining fold, say E_O. This process is repeated for all the combinations of the l folds and the final average metrics on the E_O sets are reported. In this way, the nested CV process avoids a possible bias on the model, due to the use of the same data for the model hyperparameters tuning and the model evaluation. In this study, a 10-fold Nested CV was used. In the outer layer, 10% of the data was separated for test and the rest of the data was used to develop a model. In the internal layer, the remaining 90% of the data was used for tuning the hyperparameters. Training and test sets were obtained without separating the trials consisting of 3 epochs each. In this way, the training and the test sets do not include parts of the same trial. The hyperparameters variation range are displayed in Table 5.2.

5.5 Experimental results

A within-subjects approach was realized. The accuracy (mean and standard deviation) for each classifier was assessed at varying the type of input feature. Table 5.3 shows better performances in case of features extracted from the time domain by combining Filter-Bank and CSP. In particular, the proposed solution based on 12 bandpass Filter-Bank provides the best performances for all classifiers except for LDA. In Table 5.4, the accuracy of the proposed solution is shown for each subject at varying the classifier. In case of k-NN, the mean accuracy reached the maximum value of 92.8±1.6 %. To the best of the authors' knowledge, the accuracy obtained can be considered state-of-the-art when considering a within subjects approach. Regarding rehabilitation goals, the minimization of failure in recognizing distraction is the main issue.

Therefore, an F-measure test was carried out to assess the classification

Classifier	Hyperparameter	Variation Range
k-Nearest Neighbour (k-NN)	Distance (DD)	{cityblock, chebychev, correlation, cosine, euclidean, mahalanobis, minkowski, seuclidean,spearman}
	DistanceWeight (DW)	{equal, inverse, squaredinverse}
	Exponent (E)	[0.5, 3]
	NumNeighbors (NN)	[1, 5]
Support Vector Machine (SVM)	BoxConstraint (BC)	log-scaled in the range [1e-3,1e3]
	KernelFunction (KF)	{gaussian, linear, polynomial}
	KernelScale (KS)	log-scaled in the range [1e-3,1e3]
	PolynomialOrder (PO)	{1,2,3,4}
Artificial Neural Network (ANN)	Activation Function (AF)	{relu, sigmoid, tanh}
	Hidden Layer nr. of Neurons (HLN)	[25, 200]
Linear Discriminant Analysis (LDA)	Gamma (G)	[0,1]
	Delta (D)	log-scaled in the range [1e-6,1e3]
	DiscrimType (DT)	{linear, quadratic, diagLinear,} {diagQuadratic, pseudoLinear, pseudoQuadratic}
Naive Bayes (NB)	DistributionName (DN)	{normal, kernel}
	Width (W)	log-scaled in the range [1e-4,1e14]
	Kernel (K)	{normal, box, epanechnikov, triangle}

Table 5.2: Classifier optimized Hyperparameters and variation range

CLASSIFIER	FEATURE						
	FREQUENCY DOMAIN			TIME DOMAIN			
				CSP	Filter-Bank + CSP		
	7 Traditional EEG Bands	9 EEG Bands Proposed in[85]	Proposed 12 EEG Bands		7 Traditional EEG Bands	9 EEG Bands Proposed in[85]	Proposed 12 EEG Bands
k-NN	77.5 ± 5.5	76.7 ± 5.5	80.2 ± 5.1	65.9 ± 5.0	87.4 ± 4.1	90.9 ± 3.2	92.8 ± 1.6
SVM	79.9 ± 5.6	76.0 ± 4.0	81.7 ± 6.9	69.2 ± 5.1	86.8 ± 4.5	89.8 ± 3.7	91.1 ± 3.2
LDA	76.7 ± 7.4	75.1 ± 7.2	78.3 ± 6.3	67.7 ± 4.8	82.9 ± 4.5	85.7 ± 6.2	86.6 ± 2.0
ANN	75.6 ± 6.3	73.6 ± 6.7	76.9 ± 6.4	67.2 ± 4.5	81.9 ± 4.5	85.1 ± 5.0	86.3 ± 3.5
NB	64.5 ± 6.2	63.8 ± 5.2	65.3 ± 7.8	65.2 ± 4.9	75.3 ± 7.3	77.0 ± 7.2	78.7 ± 7.5

Table 5.3: Within-subject accuracy (mean and standard deviation percentage of the 17 subject accuracy) at varying feature and classifier

Table 5.4: Within-subject accuracy of the proposed solution based on the 12 bandpass Filter Bank and Common Spatial Pattern at varying the classifier.

SUBJECT	CLASSIFIER				
	k-NN	***SVM***	***LDA***	***ANN***	***NB***
#1	91.1 ± 5.3	90.3 ± 5.2	88.2 ± 5.3	86.3 ± 7.2	66.0 ± 9.7
#2	92.2 ± 2.2	90.1 ± 5.1	85.1 ± 6.2	83.5 ± 5.3	79,2 ± 9.9
#3	93.3 ± 5.5	92.2 ± 5.1	89.2 ± 7.1	80.3 ± 7.3	87.2 ± 7.3
#4	94.1 ± 4.2	95.0 ± 2.2	89.6 ± 5.5	92.4 ± 6.8	81.3 ± 4.4
#5	90.4 ± 4.3	89.2 ± 6.7	84.3 ± 9.2	84.5 ± 7.6	65.3 ± 9.7
#6	93.3 ± 3.1	96.5 ± 3.8	91.7 ± 6.8	89.7 ± 6.2	74.1 ± 7.3
#7	96.1 ± 3.2	92.3 ± 4.4	87.2 ± 6.8	87.6 ± 8.3	80.0 ± 9.8
#8	93.1 ± 5.2	91.2 ± 6.7	88.4 ± 7.3	87.6 ± 6.1	86.5 ± 6.3
#9	91.2 ± 4.5	89.1 ± 8.8	88.4 ± 9.1	87.6 ± 6.5	82.8 ± 6.2
#10	92.1 ± 4.4	85.2 ± 4.8	80.3 ± 5.7	82.3 ± 6.9	73.2 ± 9.9
#11	91.1 ± 5.3	90.2 ± 6.7	83.5 ± 8.5	82.5 ± 9.1	79.2 ± 7.1
#12	94.8 ± 4.2	93.8 ± 3.3	91.7 ± 6.6	87.6 ± 06	87.3 ± 3.5
#13	93.3 ± 6.2	92.2 ± 7.6	84.2 ± 5.9	86.8 ± 8.4	75.6 ± 8.4
#14	96.6 ± 4.5	96.3 ± 5.3	90.8 ± 5.8	90.4 ± 6.1	86.8 ± 8.2
#15	93.8 ± 6.2	94.1 ± 4.5	88.8 ± 8.1	86.2 ± 6.5	84.4 ± 5.6
#16	93.5 ± 7.3	91.8 ± 5.5	86.6 ± 2.2	87.2 ± 5.5	82.5 ± 5.6
#17	93.2 ± 4.1	84.8 ± 6.5	77.5 ± 1.6	77.8 ± 1.1	66.4 ± 8.0
MEAN	92.8 ± 1.6	91.1 ± 3.2	86.6 ± 2.0	86.3 ± 3.5	78.7 ± 7.5

performance in minimizing false negatives for the second class (distraction) analysis. Fig. 5.3 shows a k-NN mean Recall higher than 92 %.

5.6 Proposed method

The proposed method is depicted in Fig. 5.4. The EEG signals are acquired by *Active Dry Electrodes* from the scalp. Each channel is differential with respect to AFz (REF), and referred to Fpz (GND), according to 10/20 international system. Analog signals are first transduced by the *Active Dry Electrodes* and then conditioned by the *Analog Front End*. Next, they are digitized by the *Acquisition Unit* and transmitted to the *Data Analysis* stage. Here, after an artifact removal performed by an Independent Component Analisys (ICA) based algorithm, suitable features are extracted by the chain of a 12-component *Filter Bank* and a *Common Spatial Pattern* (CSP) algorithm. Then, a classifier receives the feature arrays and detects distraction.

The EEG signal, acquired through eight channels, was filtered through a 12 IIR band-pass Filter Chebyshev type 2 filter bank, 4 Hz amplitude,

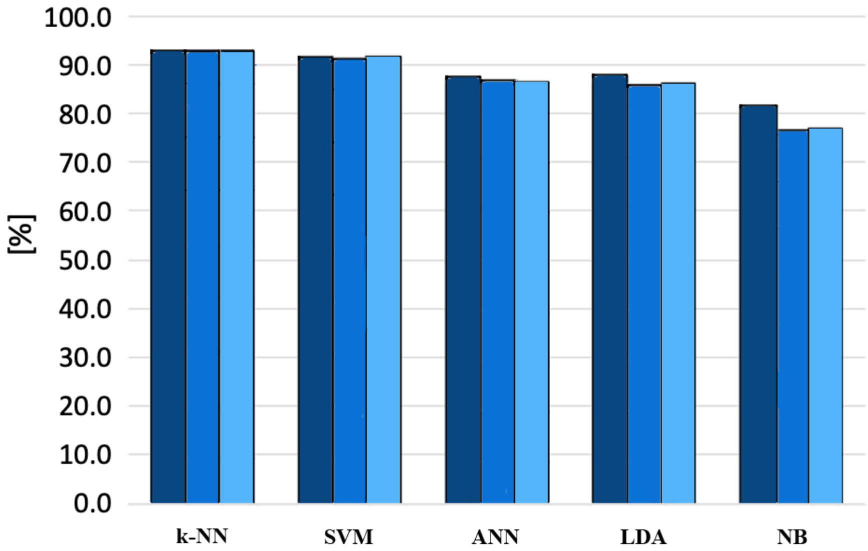


Figure 5.3: F-Measure test results for the best performance of each classifier: Precision (black) , Recall (gray), and F1-score (white).

equally spaced from 0.5 - 48.5 Hz. A filter bank with 9 filters of 8 Hz amplitude equal to [0-40] Hz, with a 4 Hz overlap, was proposed. This solution subdivided the traditional EEG beta and gamma bands into sub-bands, however combining other bands (delta and theta with the first filter between 0 and 8 Hz, as well as theta and alpha with the second filter between 4 and 12 Hz). Considering the relevance of the delta, theta and alpha bands in the analysis of the attention highlighted in Graber et al.[197] and in Coelli et al.[187], the solution proposed in this study allows to enhance their peculiar contribution. The unit of analysis of the classification activity was identified in time windows of 3 s with an overlap of 1.5 s. Considering a sampling frequency of 256 Sa/s, each of these record is therefore composed of 96 EEG tracks (obtained by applying the 12 filters of the Filter Bank on each of the 8 channels), each one of 1536 samples. A Common Spatial Pattern (CSP) was used as a spatial filtering algorithm. In this study, the CSP receives the records (epochs) as 3D tensors (channels, filters, and samples). It outputs 2D matrices (channels, filters) reducing the dimensionality of the features by a factor of 1536 (number of sample). A k-Nearest Neighbour (k-NN) classifier is used for classifying the CSP output.

This study demonstrates the possibility of using an EEG-based method already implemented in other contexts for the assessment of attention to a motor act during the execution of a dual-task. Applying this method in a walking context would provide important information for fall prevention.

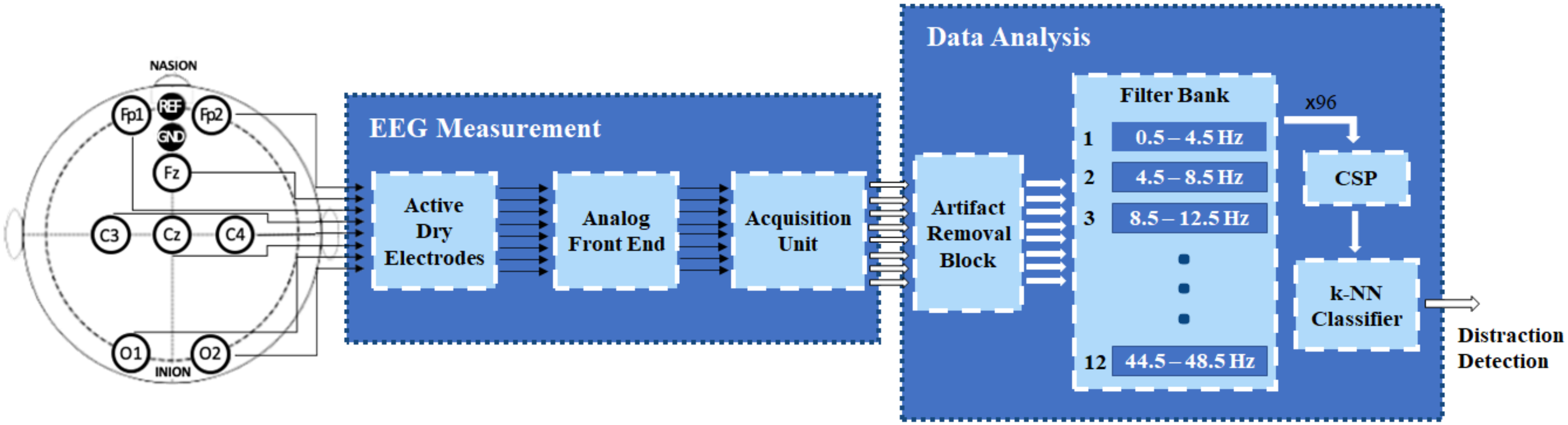


Figure 5.4: The proposed distraction-detection method (CSP: Common Spatial Pattern algorithm).

Conclusions

Due to the high costs in health care, and the high number of accidents (including fatal ones) caused by this problem, is needed to intervene to prevent falls. The gait is not an automated machanism but is the result of a complex brain processes interaction such as: (i) the cognitive engagement, (ii) the Executive Functions (EFs), and (iii) the attention. Furthermore, it is widely demonstrated that the execution of a concurrent tasks during the walk impoverishes the resources employed and contributes to enormously increase the risk of falling. For this reason, in this thesis was analyzed the neurological phenomena underlying the gait, in order to find an EEG-based method for the prevention of falls. The information deriving from the analysis of the phenomena described becomes an important index for identifying a dangerous situation for a high risk of falling.

Among EEG systems available on the market for daily use applications: the new device *abmedica*® *Helmate*, and Emotiv epoc + have been identified. A functional analysis was carried out for the Helmate to demonstrate its effective employability for the proposed applications.

A method for the detection of the cognitive load, intended as a profuse cognitive engagement in learning or rehabilitation activities has been identified. The proposed method (based on EEG-signal processing) made it possible to achieve a cognitive engagement detection on two levels (i.e., high and low): reaching an accuracy of 76.9 % in learning and 74.5 % in rehabilitation.

Starting from a literature analysis of the most studied executive functions, the employed EEG features for different EFs evaluation have been identified. Inhibition, and working-memory (and their sub-functions) are the most investigated EFs. The EEG features associated with most studied EFs are extracted about 70 % from the frequency domain.

Finally, an EEG-based detection of attention/distraction during the execution of a dual-task has been proposed. The two conditions were discriminated against with 92.8 % accuracy.

The above mentioned results confirmed the applicability of the proposed

EEG-based method for the evaluation of the phenomena underlying the walk. Through this method it is possible: to identify a situation of overload of the cognitive abilities and processing involved during the walk, and to activate an alarm of probable danger of falling.

Future developments

A further application of the proposed method consists of an EEG-based analysis of the cognitive resources employed when a subject walk during dual-task conditions. The study involves the enrollment of an experimental group and a control group: 15 healthy subjects and 15 subjects with neuromotor disorders. The participants are required to walk in four different conditions 5.5:

- free walk on the floor (fig.5.5 a);
- free walk on a planar beam (fig.5.5 b);
- free walk on the floor during dual-task execution (fig.5.5 c);
- free walk on a planar beam during dual-task execution (fig.5.5 d).

Two sessions with 5 repetitions for each task are proposed. Since the aim is to induce the subject in cognitive overload conditions during the walk, the dual-task chosen is the oddball test (see paragraph 5.3, Chapter 5). The simultaneous execution of a walk motor task and a cognitive one of counting the occurrences, allows to identify a possible condition of cognitive overload and therefore of a high risk of falling. The oddball test can be proposed both in the auditory and visual versions, in order to verify the effects on the path of different stimuli. The subjects are firstly required to take a test for an assessment of the cognitive functions. One of the possible employing test is the: Trail Making Test (TMT) type A and B. The TMT is a visuo-motor test used to verify the functionality of the subject. The TMT evaluates the spatial planning capacity in a visual-motor type task. It is extremely sensitive in detecting brain damage. Psychotic disorders, severe emotional and anxiety disorders can negatively affect part B of the test. In Italy there are two versions of the TMT:

1. AB version (the most widespread and well-known);
2. ABG version.

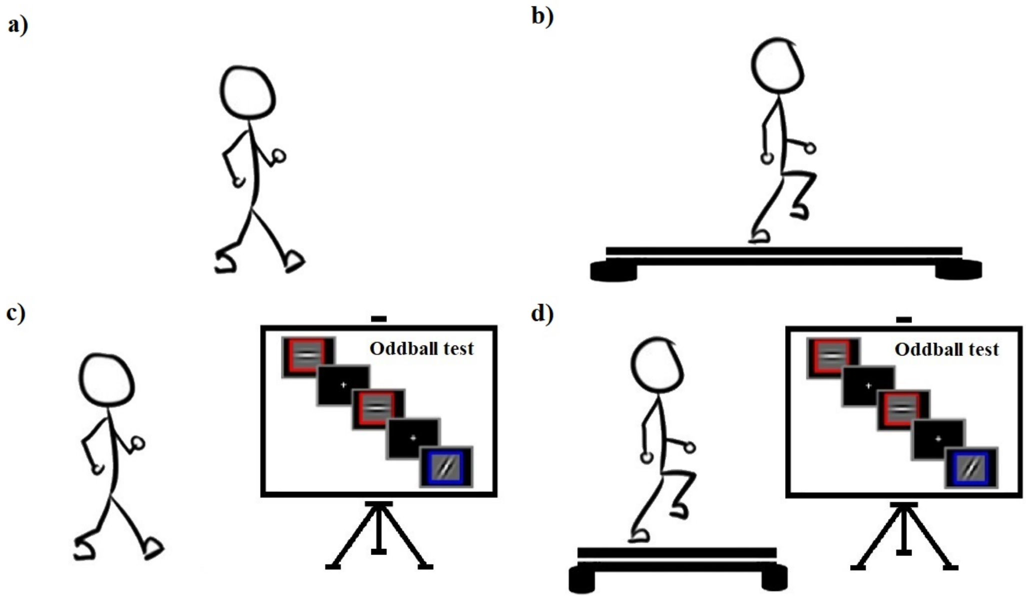


Figure 5.5: Four different task: a) free walk on the floor, b) free walk on a planar beam, c) free walk on the floor during a dual-task execution, and d) free walk on a beam during a dual-task execution.

The TMT is made up of two or three parts, A and B, and G. The correct execution of part A requires adequate visual processing skills, the recognition of numbers, the knowledge and reproduction of numerical sequences, and the motor speed. The correct performance of part B, in addition to the aforementioned skills, requires cognitive flexibility and a capacity for shifting within the norm. Part G, if used, emphasizes the previous case B in manipulating multiple stimuli simultaneously and in modifying the course of current mental activity. The time difference between the two tests (B−A) and the one (G−A) are also an index of cognitive flexibility and shifting ability.

Part A: The subject must combine the numbers from 1 to 25 in sequence with a pencil. The participant must complete the task in the shortest possible time.

Part B: The subject is presented a sheet showing 25 circles containing numbers from 1-13 and letters from A-N arranged randomly. The participant, to complete the test, must perform two tasks simultaneously: to connect both in progressive and alternating order, numbers and letters (i.e.: 1-A-2-B-3-C-, etc.), thus joining in alternating numbers (from 1 to 13) and letters (from A to N).The correct sequence is 1, A, 2, B, etc.

Part G: The subject is presented a sheet showing 8 circles, 8 squares and 8 crosses, containing respectively numbers from 1 to 8. The participant must connect the circle, the square and cross containing the number 1; then the circle, the square and the cross with the number 2, and so on.

The score is based on the number of seconds employees to complete the test. Three scores are obtained: (i) part A; (ii) part B; and (iii) difference B−A or / and difference G−A). For each part, the raw score obtained is corrected based on the subject's age and education. In relation to the obtained score, the participants are divided into two groups.

In order to assess the condition of greater risk of falling for the subject, both the performance of the cognitive task and the parameters of walking are analyzed. According to the literature, in the presence of concurrent tasks the subject reacts: reducing the stride, increasing the number of supports, obtaining worst performances in the cognitive test. *ab medica® Helmate* can be employed to collect the EEG signal (Fig.5.6 a). For the evaluation of walking parameters the G-walk and the Smart-DX by Bioengeneering G-walk can be used (Fig.5.6 b).

For the processing method part (see Fig. 5.7, the recorded EEG signal is divided into epochs, filtered and processed using an removing artifact algorithm (Independent Component Analysis) and a spatial-filtering based on a 12-Filter-banks and Common Spatial Pattern. Within-subject and cross-subject approaches can be implemented. Finally, the system can be validated through a Nested Cross Validation using different classifiers: Linear Discriminant Analysis, Support Vector Machine, k-Nearest Neighbour, Artificial Neural Network. The Accuracy, the precision, the recall, and the F1-score are employed as metrics to estimate the effectiveness of the method.

(a)

(b)

Figure 5.6: The instrumentation for the EEG signal acquisition and the gait pattern assessment: a) the Helmate provided by abmedica [80]; b)and the Smart-DX and the G-Walk provided by BTS Bioengineering [198].

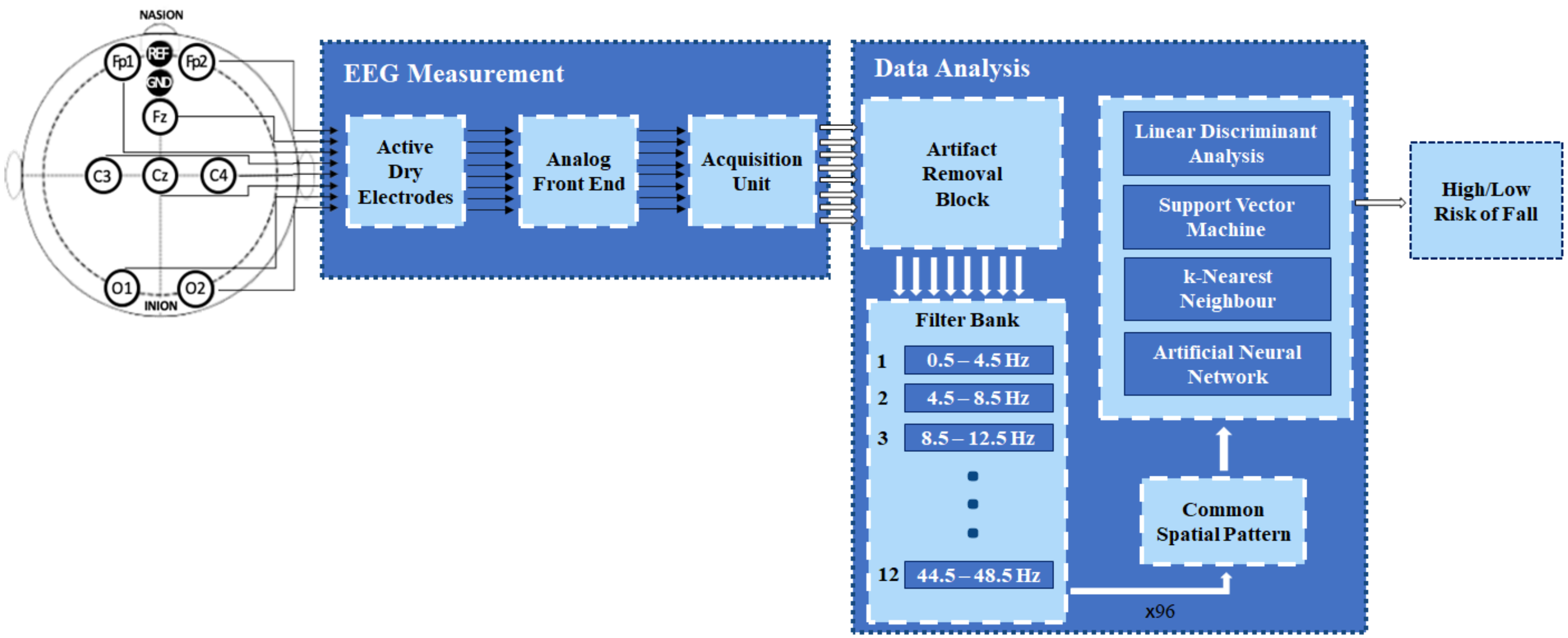


Figure 5.7: The proposed risk of fall method.

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Appendix A

Appendix on EEG functions

In this appendix, a small indication of the most used EEG features is shown. This appendix arises from the review on the EEG features most employed in the analysis of executive functions. This is not meant to be an exhaustive source, but a useful reference and an important indication for the abbreviations used in the chapter 4.

A.1 Time domain EEG features

A list of the most used EEG features in the time domain is shown below.

A.1.1 Event Related Potential - EPR

Event Related Potential (ERP) waveforms is composed of a sequence of positive and negative voltage deflections,defined ERP components. Most ERP components are named by a letter and a number. In particular, the letter refers to the positivity (P) or negativity (N) of the waves amplitude while the number indicates either the latency in milliseconds or the component's ordinal position in the waveform [199].
Some of main ERP components are shown in Fig. A.1 and are summarized in the following sections.

N1

The N1 or N100 component of ERP is a negative-going peak. It is the first substantial peak in the waveform and often occurs between 90 and 200 ms after a stimulus is presented.

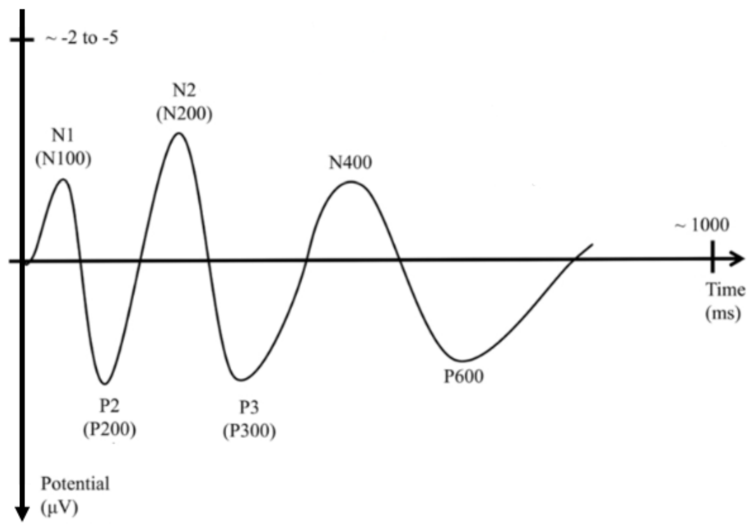

Figure A.1: ERP waveform

N2

The N2 or N200 ERP component is the second negative peak and occurs 200 ms after the stimulus.

P2

The P2 or P200 ERP component is the second positive peak and occurs around 100-250 ms after the stimulus.

P3

The P3 or P300 ERP component is the third positive peak and has a quite variable latency. Particularly, the peak of the P300 component may occur between 250 ms – 700 ms.

N400

The N400 is a negative-going deflection that peaks around 400 milliseconds post-stimulus onset, although it can extend from 250-500 ms.

P600

The P600 is characterized as a positive-going deflection with an onset around 500-600 milliseconds after the stimulus and lasts several hundred milliseconds.

Error-Related Negativity - ERN

Error-Related Negativity (ERN) is a negative component of the ERP that occurs when subjects make errors in sensorimotor tasks. The negativity peaks at around 150 msec after response onset (i. e. when one starts to make the response).

A.1.2 Contingent negative variation - CNV

The contingent negative variation (CNV) is the negative portion of the wave between the presentation of the warning and imperative stimuli.

Bereitschaftspotential - BP

The Bereitschaftspotential (BP), (from German, "readiness potential") is an event-related potential reflecting cortical activity associated with the initiation and preparation of voluntary motor actions. It is also called the pre-motor potential or readiness potential (RP). The BP is a slow negative EEG-deflection which develops beginning 1 to 1.5 s prior to the onset of a self-paced movement.

Lateralized readiness potential - LRP

The lateralized readiness potential (LRP) is an event-related potential associated with the preparation of motor activity in contralateral motor areas. The LRP reflect the preparation of motor activity on a certain side of the body. It is a spike in the electrical activity of the brain that happens when a person gets ready to move one arm, leg, or foot. The LRP is a special form of bereitschaftspotential.

A.1.3 Slow cortical potentials - SCPs

Slow cortical potentials (SCPs) are shifts in the cortical electrical activity lasting from several hundred milliseconds to several seconds. SCP might be externally triggered or self-induced.

A.1.4 Fractal Dimension - FD

Fractal Dimension (FD) is a measure of complexity degree and self-similarity of time series. There are different complexity estimators such as Higuchi, Katz, box-counting and Petrosian to calculate FD. The Higuchi's algorithm calculates FD as follows. Given an one-dimensional EEG discrete time series $x = \{x_1, ...x_N\}$ and the scale factor k, a new time series y_j^k is calculated as:

$$y_j^k = \{x(m), x(m+k), x(m+2k), ..., x(m + [\frac{N-m}{k}]k\} \tag{A.1}$$

for m = 1, 2, 3, ..., k. Where [.] indicates the integer part of series The length L_m^k is computed for y_j^k as:

$$L_m^k = \frac{\sum |y(m+ik) - y(m+(i-1)k|(N-1)}{[\frac{(N-m)}{k}]k} \tag{A.2}$$

where N is the number of samples in the time series. FD is calculated as total average length, L(k), for k_1 to k_{max}.

A.1.5 Multiscale Entropy - MSE

The multiscale Entropy (MSE) method has been used to quantifies the complexity of signal by calculating the sample entropy (SampEn) over multiple temporal scales which was realized by coarse-grained procedure (Costa et al., 2005, Costa et al., 2002). Given an one-dimensional EEG discrete time series $x = \{x_1, ...x_N\}$ and the scale factor τ, the time series is calculated in to consecutive and nonoverlapping time series y_j^τ as:

$$y_j^\tau = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i; 1 \leq j \leq \frac{N}{\tau} \tag{A.3}$$

And then calculates the SampEn of each series y_j^τ as:

$$SampEn(m, r, N) = -\ln \frac{C^{m+1}}{C^m}; C^m = numberofpairs(i, j), i \neq jwhere|y_i^m - y_j^m| < r \tag{A.4}$$

where $|y_i^m - x_y^m|$ denotes the distance between vectors y_i^m and y_j^m, m is dimension of vectors y_i^m and y_j^m and r is the tolerable distance between the two vectors and N represents the length of the time series.

A.1.6 Lempel–Ziv complexity - LZC

Lempel–Ziv complexity (LZC) is a popular measure for characterizing the complexity of biomedical signals (Fernández et al., 2011; Méndez et al., 2012; Nagarajan, 2002; Zhang, Roy, Jensen, 2001). To compute the LZC, the oscillations of a time series have to be transformed into a binary sequence. The simplest approach is to convert the time series x(k), k = 1, . . . n, into a 0–1 sequence by comparison with a threshold T_d as follows:

$$s(i) = \begin{cases} 1 & \text{if } x(i) < T_d \\ 0 & \text{if } x(i) \geq T_d \end{cases} \tag{A.5}$$

A good choice for T_d is the median value of the signal in each electrode, because it is robust to outliers (Hu, Gao, Principe, 2006; Nagarajan, 2002). Then, the sequence P is scanned, and a complexity counter, c(n), is increased by one unit each time a new subsequence of successive characters is encountered in the scanning process. Finally, normalized LZC is defined by

$$C_{LZ} = \frac{\log_2 nc(n)}{n} \tag{A.6}$$

A.1.7 EEG valid rate - EEGVR

The EEG valid rate (EEGVR) is an index to investigate attention function in the subjects. It is the ratio of artifact-free EEG epochs divided by total epochs.

A.1.8 Weighted phase-lag index - WPLI

The weighted phase-lag index (WPLI) is a measure of phase-synchronization.It is defined as:

$$\Phi = \frac{|E\{J(X)\}|}{E\{J(X)\}} \tag{A.7}$$

where J(X) denotes the imaginary component of the cross-spectrum.

A.2 Frequency domain EEG features

In the frequency domain there are 6 different sub-domains identified by the known bands of the EEG signal: δ [0.1 - 3] Hz, θ [4 - 7] Hz, α [8 - 12] Hz, β [16 - 31] Hz,γ [32 - 100] Hz, and μ [9 - 11] Hz (in sensorimotor cortex). The features described find applications in each of the sub-domains or in combinations of them.The list of the most used EEG features in the frequency domain is shown below.

A.2.1 Power spectral density/Relative power spectral density

The power spectral density (PSD) represents the power distribution of EEG series in the frequency domain. The power spectral density (PSD) of EEG signal can be calculated into each six EEG sub-bands. In general, Welch's method (a modified approach of FFT), FFT method, and Burg's method may be regarded as the three most widely used methods for PSD estimation within a frequency band in EEG. Relative PSD is defined as the ratio of the PSD to the frequency band to be analyzed and the total frequency band.

A.2.2 Modulation index - MI

The alpha modulation index (MI) is computed by subtracting alpha power in right-cued trials from left-cued trials for each electrode. This subtraction was subsequently normalized by dividing by half of the sum of these values:

$$MI = \frac{(\alpha_{leftcuedtrials} - \alpha_{rightcuedtrials})}{(\frac{1}{2}\alpha_{leftcuedtrials} + \alpha_{rightcuedtrials})} \tag{A.8}$$

A.2.3 The EEG Consistency Index - CI

Discrete spectra, including residual power, are calculated for all EEG channels. Power change distances (PCD) between two contiguous tasks are computed for each EEG band and channel. PCD undergo filtering to eliminate changes below a *noise threshold*. The noise threshold works as follows: the larger PCD of an absolute value than the threshold are marked by 1 or -1 depending on their direction, whereas all PCD below threshold are marked by zero. This filtering transforms the PCD into a sequence of 1,0,-1 that indicates, for each EEG band and channel, whether a significant power change was observed while the person shifted from one task to another. The final pass of the computation is a simple addition of the filtered PCD below and above the cutoff value. The the EEG Consistency Index (CI) is defined as the absolute value of the difference between these two PCD-based sums, expressed as a percentage, i.e., computed using the formula:

$$CI = 100|\frac{1}{2}(\sum_{belowcutoff} \delta_i - \sum_{abovecutoff} \delta_j)|\% \tag{A.9}$$

where δ_i, $\delta_j = -1,0,1$

A.2.4 Asymmetry index - AI

The asymmetry index (AI) represents the balance between left and right brain activities. it can be calculated for each of the frequency bands / subdomains of the EEG signal. As an example, we report the AI for the α band:

$$AI = \frac{Alpha_(RightHemisphere) - Alpha_(LeftHemisphere)}{Alpha_(RightHemisphere) + Alpha_(LeftHemisphere)} \tag{A.10}$$

(This α-AI is the most used in EFs evaluation).

A.2.5 Theta-beta ratio - TBR

The Theta-beta ratio (TBR) is the ratio between the power spectral density in θ band and the power spectral density in β band.

$$AI = \frac{PSD_\theta}{PSD_\beta} \tag{A.11}$$

A.2.6 Sensorimotor rhythms - SMR

Sensorimotor rhythms (SMR) are brain signals associated with motor activities, e.g. limb movements. The SMR consist of EEG oscillations measurable in the μ and β bands, typically corresponding to the 8 Hz to 13 Hz and 13 Hz to 30 Hz ranges.

A.2.7 The EEG Concentration Index

The EEG Concentration Index in the EFS context, is defined as the sum of sensory motor rhythms and $\beta/\ \theta$ wave ratio.

Some of the previous informations has been available in:
Pasquale Arpaia, Loredana Cristaldi, Mirco Frosolone, Ludovia Gargiulo, Francesca Mancino, Nicola Moccaldi, *"EEG features of executive functions employed in the diagnosis and treatment of children with ADHD: a review."*, to be submitted to Topics in cognitive science, 2021, Wiley-Blackwell.

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