ACTA IMEKO
ISSN: 2221-870X
June 2023, Volume 12, Number 2, 1 - 6

Electroencephalographic-based wearable instrumentation to monitor the executive functions during gait: a feasibility study

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ABSTRACT
A feasibility study on electroencephalographic monitoring of executive functions during dual (motor and cognitive) task execution is presented. Electroencephalographic (EEG) signals are acquired by means of a wearable device with few channels and dry electrodes. The light weight and wireless device allow for walking in a natural way. The most significant EEG features are investigated to classify different levels of activation for two fundamental Executive Functions (EF) both in sitting and walking conditions. Power spectral density in the gamma band resulted in the most relevant feature in discriminating low and high levels of Inhibition. Power spectral density in the beta and gamma bands resulted the most discriminating the level of activation of Working Memory. The study poses the basis for (i) monitoring the activation levels of EF during Gait allowing loss prevention in the elderly and (ii) specific cognitive rehabilitation aimed at the most relevant executive functions during walking.

Section: RESEARCH PAPER

Keywords: executive function monitoring; wearables; brain computer interface; dual task; electroencephalographic features

Citation: Pasquale Arpaia, Renato Cuocolo, Paolo De Blasiis, Anna Della Calce, Allegra Fullin, Ludovica Gargiulo, Luigi Maffei, Nicola Moccaldi, Electroencephalographic-based wearable instrumentation to monitor the executive functions during gait: a feasibility study, Acta IMEKO, vol. 12, no. 2, article 10, June 2023, identifier: IMEKO-ACTA-12 (2023)-02-10

Section Editor: Francesco Lamonaca, University of Calabria, Italy

Received January 27, 2023; **In final form** March 2, 2023; **Published** June 2023

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1. INTRODUCTION

The performance of most motor tasks requires the use of cognitive resources [1]. Cognitive resources, also called Executive Functions (EFs), are a set of neurocognitive processes necessary for the organization, planning and regulation of daily life actions [2]. According to Diamond et. al [3], the basic EFs are working memory, i.e., the ability to keep in mind information, inhibition, i.e., the ability to interrupt a motor and/or cognitive response no longer appropriate to the circumstances, and the cognitive flexibility, i.e., the ability to adapt to rapidly varying circumstances. The more demanding an activity, the greater the cognitive demand.

Humans are involved in the simultaneous performing of several activities most of the time. It is common for humans to walk and talk on their mobile phones at the same time, or play sports and listen to music. According to the attentional capacity theory, humans have limited cognitive capacity, so when the performed activities require cognitive resources that exceed those available, there is a decrease in performance quality [4]. Moreover, if a task is too demanding and the required brain resources exceed a certain threshold, cognitive processing of further tasks may be precluded [5]. Therefore, understanding how cognitive resources are allocated during tasks is crucial and allows improving the user-task interaction by adapting the task to the cognitive state [6]. The cost of performing a dual task is greater in the elderly and in people with neurodegenerative conditions; therefore, monitoring how cognitive resources are allocated in a dual task context is particularly useful. In these people, cognitive resources and the ability to allocate them properly are limited. Therefore, monitoring a condition of cognitive resources fatigue makes it possible both to predict risks (i.e., risk of falling), and to set up rehabilitation interventions aimed to strengthen the cognitive resources and their correct allocation [4]. Neurophysiological measures are particularly suitable for monitoring cognitive resource fatigue in a dual-task context as they provide direct and continuous information on the subject's brain state. Among them, electroencephalographic (EEG)-based methods are becoming increasingly important due to their high temporal resolution and good real-time performance [7]. Moreover, wearable devices are becoming more and more reliable in signal acquisition [8], [9], also allowing monitoring of EEG outside laboratories and clinical settings [10], [11], [12], [13].

Several bio-markers linked to the activation and fatigue of the basic executive functions are proposed in the literature. In particular, EEG Power Spectral Density (PSD) have been extensively studied [14], [15] in Fz, Cz, Pz, Fz, C3 [16], [17], [18], [19] but the link between activation and fatigue of a particular executive function and the PSD is not yet unambiguously defined. This study investigates the neural correlates of Executive Functions during a dual task execution. The use of a highly wearable device minimizes the interferences on the execution of the ambulation in a spontaneous way. In particular, the aims are (i) EEG-based identification of working memory and inhibition activation during walking, and (ii) the investigation of the most informative EEG features about activation levels of a specific executive function.

2. MATERIAL AND METHODS

2.1. Experimental sample

Five healthy males voluntarily chose to participate in this study. The following inclusion criteria were: age (20, 30), BMI < 25 kg/m², absence of pain, no surgeries in the last 6 months, no muscle-skeletal injuries in the last 3 months, no skeletal dysmorphism and no cognitive impairment. They were all right-handed and able to understand the purpose of this study. All the volunteers were informed in detail about the objectives of the project. Subjects authorized inclusion in the study by signing the informed consent form. In accordance to the declaration of Helsinki, ethical approval was obtained from the Ethics Committee of Psychological Research of University of Naples Federico II.

2.2. Hardware and Software

EEG data acquisition were acquired by the abmedica Helmate system. It is a wireless Class II A device used for EEG signal measurements [20]. It consists of an ultralight foam helmet capable of performing EEG-signal acquisition by means of dry electrodes. Helmate provides 10 dry electrodes arranged according to the international 10/20 positioning system: Fp1, Fp2, Fz, Cz, C5, C6, O1, O2, AFz (ref), and Fpz (Ground). A custom software was realized to provide the cognitive tasks and monitor and store the EEG signal [18]. Quantitative evaluation of walking was performed using an optoelectronic system composed of eight Smart-D cameras (BTS Bioengineering, Italy) set at a frequency of 100 Hz and two force platforms (BTS Bioengineering-Milano, Italy). Helen Hayes M.M. markers set protocol was used for 3D-stereophotogrammetric analysis [21].

2.3. Experimental protocol

Participants entered a very quiet room and were explained the experimental protocol. After the subject sat down on a comfortable chair, the EEG-acquisition system was set up. The subject held a wireless controller with his right hand to perform cognitive tasks. The wireless controller was used instead of the vocal response to minimize muscular artifacts. Cognitive tasks employed for this study were:

- Go-No Go task: participants were required to either respond (i.e., pressing designated key) or inhibit a response (not pressing designated key) depending on whether a go stimulus or a no-go stimulus was presented. The difficulty of the task increased by reducing the time between stimuli. The task predominantly activates inhibition.
- N-back task: participants were presented a sequence of stimuli (i.e., a sequence of letters) one-by-one. For each stimulus, they needed to decide if the current stimulus was the same as the one presented N trials before. The load factor N varied according to the difficulty of the task. The task predominantly activates working memory.

Task stimuli were provided acoustically to allow the subject to perform the task in motion. The study was divided into ten experimental trials for a total duration of approximately one hour. The recording of the EEG signal was carried out during the following conditions:

- While the subject was seated and relaxed, preventing head movements. (1 minute);
- While sitting and performing Go-No Go task at the first level of difficulty (5 minutes);
- While sitting and performing Go-No Go task at the second level of difficulty (5 minutes);
- While sitting and performing N-back task at the first level of difficulty (1 minute);
- While sitting and performing N-back task at the second level of difficulty (1 minute);
- While walking naturally (1 minute);
- While walking and performing Go-No Go task at the first level of difficulty (5 minutes);
- While walking and performing Go-No Go task at the second level of difficulty (5 minutes);
- While walking and performing N-back task at the first level of difficulty (1 minute).

While walking and performing N-back task at the second level of difficulty (1 minute).

The kinematic patterns were assessed for each subject, while walking barefoot on a 6 m walkway at a self-selected normal paced speed. At the end of the experiment, the subjects were asked to fill in two questionnaires:

- System Usability Scale (SUS) to assess the usability of a system. It consists of a 10-item questionnaire with five response options, ranging from Strongly Agree to Strongly Disagree;

The NASA Task Load Index (NASA-TLX) for the workload assessment. It consists of a 6-item questionnaire, rated within a 100-points range. The workload is rated across six dimensions (mental demand, physical demand, temporal demand, effort,

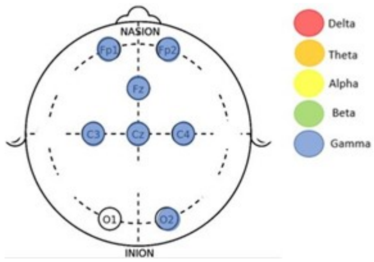


Figure 1. Sequential Feature Selector Color-map in comparing sitting baseline and walking baseline.

performance, frustration level) to determine an overall workload rating.

2.4. EEG data processing

In the pre-processing phase, data were filtered by a fourth order bandpass Butterworth filter [0.5 - 45] Hz and the Artifact Subspace Reconstruction (ASR) [22] procedure was applied with a cut off equal to 15 to remove artifacts. The ASR is a component-based artifact removal method suitable for removing transient or large-amplitude artifacts. The ASR decomposes a signal into components, then automatically identifies a threshold, based on the distribution of the signal variance; finally, it rejects the noisy components above the threshold and reconstructs the signal by considering the remaining components. Then EEG tracks are divided into 1–s epochs and PSD in alpha ([8-13] Hz), theta ([4-8] Hz), beta ([13-20] Hz), gamma ([30-45] Hz) and delta ([1-4] Hz) bands is computed.

In the features selection phase, the Sequential Feature Selection (SFS) [23] is applied in order to identify the most significant features to discriminate among different conditions. The Support Vector Machine is the classifier adopted within the SFS. In particular, the selection of the most significant features is carried out for the following cases:

(i) sitting baseline and walking baseline,
(ii) sitting baseline and sitting easy N-Back execution,
(iii) sitting baseline and sitting difficult N-Back execution,
(iv) sitting easy N-Back execution and sitting difficult N-Back execution,
(v) sitting baseline and sitting easy Go-No Go execution,
(vi) sitting baseline and sitting difficult Go-No Go execution,
(vii) sitting easy Go-No Go execution and sitting difficult Go-No Go execution,
(viii) walking baseline and walking easy N-Back execution,
(ix) walking baseline and walking difficult N-Back execution,
(x) walking easy N-Back execution and walking difficult N-Back execution,
(xi) walking baseline and sitting easy Go-No Go execution,
(xii) walking baseline and walking difficult Go-No Go execution, and
(xiii) walking easy Go-No Go execution and walking difficult Go-No Go execution.

Finally, the acquired data were divided into 1-s epochs, organized in the form [Epoch x Channel x Band] and were given in input to the SFS.

Table 1. Cognitive task performances.

Task	Condition	Percentage of correct answers (%)
Easy Go-No Go	Sitting	99 ± 1
	Walking	100 ± 0
Difficult Go-No Go	Sitting	99 ±2
	Walking	97±2
Easy N-Back	Sitting	98 ± 2
	Walking	97±3
Difficult N-Back	Sitting	94 ±2
	Walking	92 ± 6

3. RESULTS

The SFS results are reported in the colour-map of Figure 1, Figure 2, Figure 3, Figure 4 and Figure 5 for each comparison. For each binary problem, channels are coloured if a band resulted the most discriminating for at least 3 out of 5 subjects. Motor performances did not statistically differ between conditions. This could be due to the small sample size.

Also on cognitive performances, no statistical relevant differences emerged. However, results (Table 1) confirmed a high level of engagement in performing the required tasks.

The overall mean accuracies for discriminating difficulty levels were (63.7 ± 7.8) % and (63.9 ± 6.3) % for Go-No Go and N-Back, respectively.

4. DISCUSSION

According to the literature, PSD in gamma and beta band increases in all cognitive processes requiring attention [24], [25] and activation of mnestic processes [26], [27]. In Figure 1, results on the most discriminating features between a condition of motor inactivity and one of motor activity are shown. PSD in the gamma band turns out to be the most discriminating feature in 3 out of 5 subjects in Fp1, Fp2, Fz, C3, C4, Cz and O2. Motor activity requires activation of the areas responsible for walking and movement. An increase in power spectral density in the fast bands (beta and gamma) in the motor area and in the prefrontal area is expected when a subject is involved in a motor activity. Therefore, the results are consistent with expectations. In Figure 2, the beta- and gamma-band PSDs best discriminate the resting condition from that of cognitive activation due to the performance of the N-Back.

These results are consistent with expectations since the N-Back is a concentration and memory exercise and the beta band is linked to attention [25], concentration and motor programming [28], [29] while the gamma band is related to memory processes [26], [27]. The N-Back also requires acoustic attention, therefore, some form of activation is expected in the Brodmann area presiding over acoustic signal processing. In particular, an increase in the fast bands (beta and gamma) resulted at C3 and C4, the available channels nearest to the temporal area, responsible for processing acoustic information. In the occipital area, the PSD in alpha band emerges. The alpha rhythm is considered a thalamus-cortical or cortico-cortical interaction rhythm [30] and it is likely that a decrease in the alpha band occurs as a result of the cognitive engagement in demanding tasks [31]. As far as the two difficult level of Go-No Go task execution and its comparisons with the sitting baseline is concerned (Figure 3), the most significant feature is the PSD in the gamma band. This result is also consistent with the previous statements.

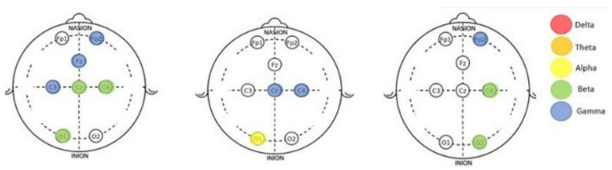
In the case of the comparison between the baseline acquired during walking and the N-Back and the N-Back tasks at two level of difficulties performed in motion (Figure 4), the discriminability between the various conditions seems to be related also to the delta and theta bands as well as alpha, gamma and beta. The delta-band PSD variation is probably due to motion artefacts, and frontal theta-band PSD variation could also be due to eye movements.

Therefore, as far as memory is concerned, no discriminative elements emerge during walking and the function is not stressed enough to stand out against the background noise. The noise conditions between the two experiments were statistically comparable after a t-test application (p-value = 0.27). Finally, as far as the comparison between the two level of difficulties of Go-No Go performed in walking and the walking baseline comparison is concerned, the PSD in gamma and beta bands in the frontal and motor area are the most discriminative features, consistently with what emerges when the subject is seated.

However, the experiment is not pure from Executive Function overlaps that are not the subject of this study, because each proposed task does not only stimulate memory or inhibition. In fact, the acoustic channel is also employed by the proposed tasks, and thus there is a co-activation of neuronal systems of various areas that communicate with each other, e.g. the Brodmann area that processes the acoustic signal. In the case of walking, it can be concluded that the activation of memory is not discriminable while that of the inhibition function emerges more clearly.

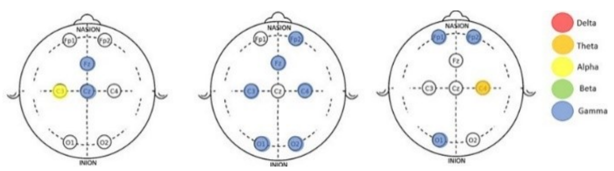
Due to limitations of the EEG device, some areas, such as temporal areas, responsible for mnestic processing, are not available. In a future study, PSD in beta2 band ([21-30] Hz) will be focused on, as it is the one mainly related to mnemonic and attentional processes.

In the future, it could be interesting to exploit more wearable sensors for monitoring also gait [32] and/or further biosignals [33], [34].



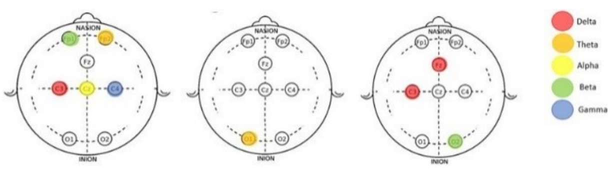
(a) (b) (c)

Figure 2. Colormaps of SFS-detected EEG features, prevalent among participants, in a seated set-up when the working memory is stimulated. Three comparisons are reported: (a) baseline easy N-Back, (b) baseline difficult N-Back, and (c) easy N-Back and difficult N-Back.



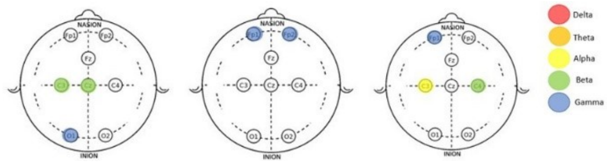
(a) (b) (c)

Figure 3. Colormaps of SFS-detected EEG features, prevalent among participants, in a seated set-up when the inhibition is stimulated. Three comparisons are reported: (a) baseline and easy Go-No Go, (b) baseline difficult Go-No Go, and (c) easy Go-No Go and difficult Go-No Go.



(a) (b) (c)

Figure 4. Colormaps of SFS-detected EEG features, prevalent among participants, in a walking set-up when the working memory is stimulated. Three comparisons are reported: (a) baseline easy N-Back, (b) baseline difficult N-Back, and (c) easy N-Back difficult N-Back.



(a) (b) (c)

Figure 5. Colormaps of SFS-detected EEG features, prevalent among participants, in a walking set-up when the inhibition is stimulated. Three comparisons are reported: (a) baseline easy Go-No Go, (b) baseline difficult Go-No Go, and (c) easy Go-No Go difficult Go-No Go.

5. CONCLUSIONS

The neural correlates of Executive Functions were investigated during dual task execution. The use of a highly wearable device guaranteed the execution of the ambulation in a spontaneous way. Different degrees of involvement for working memory and inhibition were classified by means of different machine learning algorithms. A sensitivity analysis revealed the EEG features maximizing the classification accuracy. Power spectral density in the gamma band is the most relevant feature in discriminating between low and high levels of Inhibition. An equally high level of discrimination between high and low levels of activation of Working Memory is not reached. This study is a first step towards the implementation of a fall prevention system and represents a contribution to a more targeted definition of cognitive rehabilitation interventions.

Further studies will be carried out by using devices with more electrodes also in the temporal areas to better monitor mnestic processes and by focusing on beta2 band.

ACKNOWLEDGEMENT

This work was carried out as part of the “INTENSE” project, which was financially supported by the Italian Ministry of Economical Development, (MISE). The authors thanks Andrea Pollastro for the software implementation.

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