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THE WORKING MEMORY ASSESSMENT OF VISUAL IMPAIRED PERSONS – A STUDY CASE

BY

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Abstract. In this paper, a framework for assessing the short term working memory activity of blind and visually impaired people in concordance with the n-back test is presented. Due to the particular way in which blind people perceive environmental stimuli the standard n-back tests are not applicable therefore the experimental setup and the software architecture of the framework were tailored for various audio stimuli in English and Romanian. The working memory activity and cognitive load evaluation were based on Brain-Computer Interface techniques. A significant number of tests with volunteers, sighted and unsighted peoples, were performed using the developed framework, and a significant data set containing the electroencephalogram waves acquired during the experiment was created. The raw signals were processed offline in order to explore the most suitable features for working memory assessment. Some classification algorithms were used for cognitive load discrimination and the obtained results were in accordance with theory and validate the experimental dataset used.

Keywords: EEG; cognitive load; classification; audio stimuli; n-back test.

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1. Introduction

The statistics reported by World Health Organisation reveal that blindness and vision impairment affect at least 2.2 billion people around the world, with major effects on all aspects of life (World Health Organization, 2020). Among the daily personal activities, the navigation of a Visually Impaired Person (VIP) in either an unknown or a familiar environment represents a permanent challenge and a continuous source of stress, concentration, and effort of memorizing the corresponding paths (Coulacoglou and Saklofske, 2018). There are various mobile and desktop applications specially designed to ease VIP interaction with the community, to access education or public services. Also, there are navigation systems developed for guiding VIPs navigation on indoor or outdoor routes, the top range ones being those based on Sensory Substitution Devices (SSD). SSDs create and convey an auditory and/or tactile representation of the surrounding environment (Ungureanu *et al.*, 2017a). The work presented in this paper is part of a research focused on assessing the cognitive and emotional activity of VIPs in relation to the usage of a SSD, using the Brain-Computer Interface (BCI) techniques (Ungureanu *et al.*, 2017a; Sound of Vision, 2020). The evaluation of working memory (WM) and cognitive load (CL) is usually investigated by comparing the brain activity or the scores obtained by users along specific tasks conducted according to the n-back paradigm which is extensively used in BCI research (Ungureanu *et al.*, 2019; Martin, 2014; Meule, 2017). During the n-back tasks, random sequential stimuli are individually presented to the test subject. The subject must recognize the stimulus which appeared in n = 1, 2 or 3 trials before (as pictured in Fig. 1) and press a button if the stimuli match is respected according to the performed test (Farnsworth, 2020).

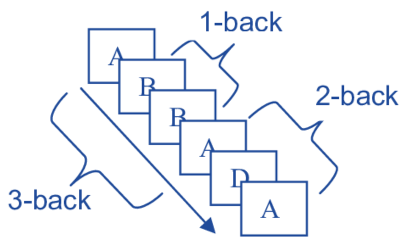

Fig. 1 – The concept of the n-back paradigm.

Most studies in the field involve the separate use of visual or audio stimuli, although some use dual-shape combinations applied to different test scenarios. The existing free online applications for n-back task simulation offer the possibility of configuring settings like the test type, the stimuli, the duration, and so forth. At the same time, they provide some insightful feedback information at the end of the test, like the number of correctly repeated sequences, or test score (Dual N-Back, 2020; Cognitive Fun, 2020). Customizable audio n-back tasks are accessible for free, but they are efficiently used only for English speaking users (Monk *et al.*, 2011).

In the given context, the main goal of this research is represented by the development of a framework for performing WM and CL assessment via EEG data acquired during audio n-back tasks designed for Romanian speaking users that have a visual impairment.

2. Framework Description

Concerning the design and implementation, the proposed framework consists of a BCI system for EEG signal acquisition and pre-processing, a web application for performing n-Back tasks, and two Python modules: one for data analysis and database development and another one for feature extraction, classification and visualization as illustrated in Fig. 2.

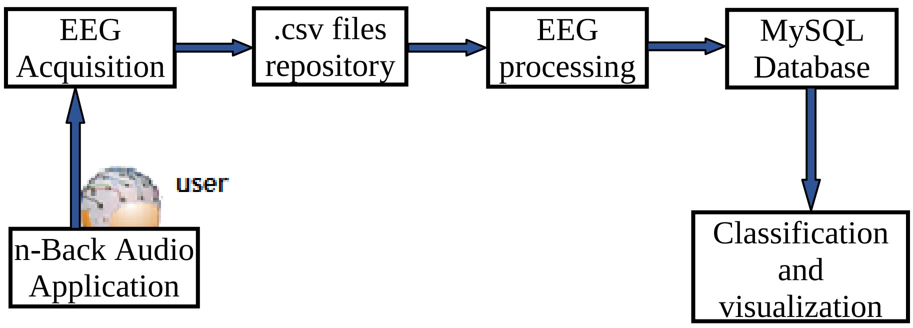

Fig. 2 – The architecture of the proposed framework.

2.1. Data Acquisition and Signal Processing

The EEG acquisition equipment includes a Vamp-16 amplifier provided by BrainProducts (Brain Products, 2020) and an adjustable silicone EasyCap headset with passive wet 30 Ag/AgCl electrodes. The electrodes are placed according to the 10-20 International System: FP1, F7, F3, C3, P3, T7, O1, O2, F8, F4, C4, P4, T8, FP2, AFz as ground and reference on the right ear lobe. The EEG waves were recorded at a 512 Hz sample rate and filtered with an analog bandwidth of 0.01 – 100 Hz Butterworth filter. For acquiring reliable EEG raw data, the impedance of each electrode must be maintained below 5 kΩ (Fig. 3). This was a key task since we did not use specific algorithms for artifact rejection mainly due to the fact that the VIPs do not blink or activate their face muscles and usually they had a rigid posture without head movement.

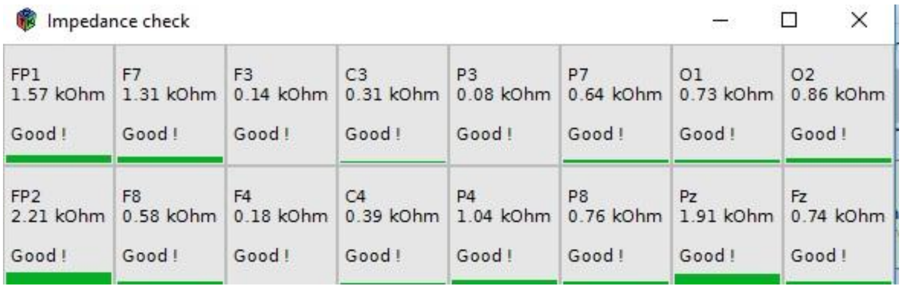

Fig. 3 – Impedance check of the electrodes.

According to our knowledge and experience, the wet electrodes (saline or gel) remain the gold standard for clinical and non-clinical EEG recordings and they are privileged by most of the trained technicians (Hinrichs *et al.*, 2020) despite the dry electrodes which are preferred by users and need a shorter time for mounting and setup. At the time of the experiments, we also used a helmet with dry electrodes compatible with the BrainProducts amplifier, but it could not ensure good contact with the scalp without an uncomfortable pressure on the user's head. Data loss were identified and some differences between signals acquired with wet and dry electrodes in rest tests were observed, especially in alpha band. Finally, the EasyCap helmet with wet 30 Ag/AgCl electrodes was a suitable choice for all experiments carried out along the project.

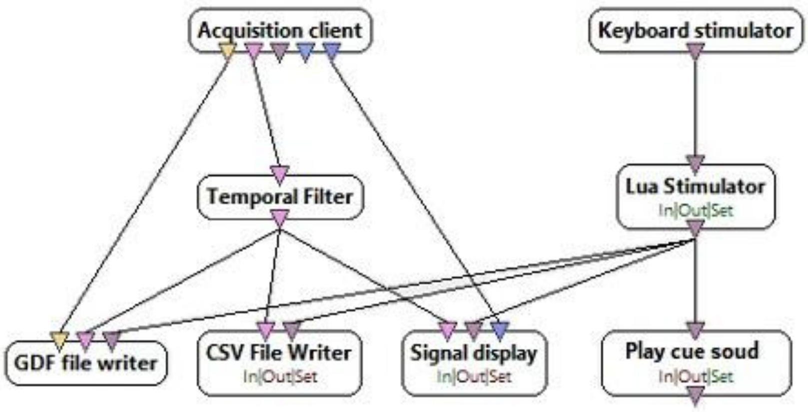

Fig. 4 – The Designer diagram for acquisition and synchronization with audio stimuli.

The software application is implemented using the open-source OpenVibe environment (Open Vibe, 2020). The acquisition server acquires signals according to the setup experiment and the acquisition client is started from the Designer custom application (Fig. 4). The acquired signals are synchronized with different events associated with audio stimuli with the help of the Lua Stimulator module. Mainly, the Designer application displays in real-time the acquired cortex waves and saves the raw data in some file formats (.csv, .gdf) for further offline processing.

2.2. The N-Back Audio Module

The EEG signals are continuously acquired during the n-back memory task execution. The n-back Audio Application allows the test taker to select the sound package to be used, the response time for a question, the number of sounds played until the evaluation is completed, and the value of ***N*** from n-back. After starting the test, the application scans the selected test folder and creates a vector with all the files. A new vector of the size mentioned in the previous step is created and populated with random values from the file vector. After this step, a vector with the correct answers is provided. The answer to the current question is correct if its value is identical to that of the value that appeared N positions back. Only if the total number of possible correct answers is less than 2, this vector is recalculated.

The application contains 6 sound packages:

- Letters 1 – contains the letters: “a”, “e”, “g”, “l”, “o” pronounced with a British accent Men (Sample Swap, 2020)
- Letters 2 – contains the letters: "h", "i", "p", "t", "u" pronounced with a British accent Men
- Impact 1 – a set of 6 ambient sounds
- Impact 2 – a set of 6 ambient sounds
- Letters RO 1 – contains the letters: “a”, “e”, “g”, “l”, “o” pronounced in Romanian
- Letters RO 2 – contains the letters: „h”, „i”, „p”, „t”, „u” pronounced in Romanian
- Words RO 1, Words RO 2 – two sets of different 6 words pronounced in Romanian

The audio samples were selected from free repositories (Sample Swap, 2020; Pelle, 2020). The N-back Audio Application was implemented using Html 5, CSS3, JavaScript and PHP. For easier data handling, the Bootstrap library was used for the designing the elements on the webpage. The jQuery library was used to dynamically generate questions, scroll through them, check the correct answers and record them.

The PHP script receives the input data from the interface, scans the document folder and generates the correct question and answer vectors, and then returns the results in JSON (JavaScript Object Notation) format, suitable for data interchange.

The application interface contains two tabs for *Times to play* and *Time per question (ms)* selection, two drop-down lists used to select the desired sound set and the n-back task and the Start button. The interface has no significance for the visual impairment users thus its design is very simple.

2.3. The EEG Processing Module

The EEG processing module was implemented in Python - Anaconda 3 distribution using some additional libraries: NumPy, Matplotlib, Pandas, MySQL Connector, SciPy, NME. The script intended for pre-processing EEG data in the .csv files followed some classical techniques: involving a Notch filter for removing the power line of 50 Hz, a Savitzky – Golay smoothing filter (Cîmpanu *et al*., 2017; Ungureanu *et al*., 2019), and the baseline-normalization using the resting state record. Then, Chebyshev band-pass filters were used to obtain frequency bands of interest: delta (0.5,...,4 Hz), theta (4,...,7 Hz), alpha (8,...,12 Hz), beta (12,...,30 Hz), and gamma (30,...,70 Hz). For each EEG frequency band, different features were calculated in time and frequency domains. The power spectrum of brain signals in each band is essential for calculating the cortex asymmetry (especially the frontal one), which reflects the cognitive load and the valence for audio stimuli.

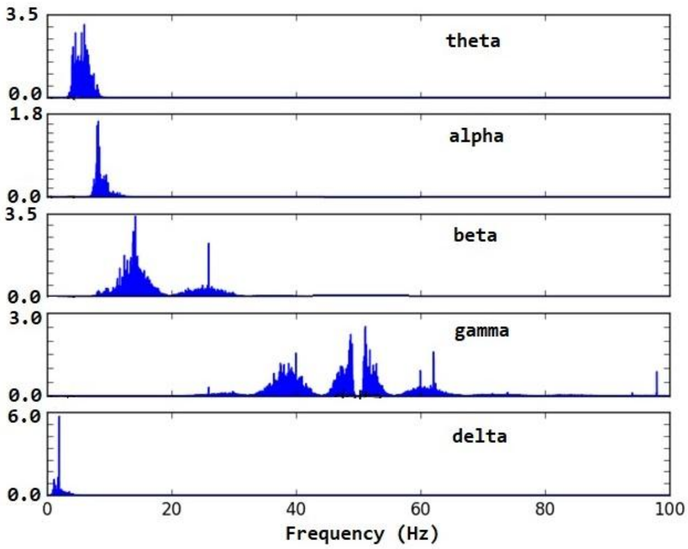

Fig. 5 – Power spectrum for EEG bands.

In Fig. 5, the power spectrum for the F4 electrode during a 2-back task is shown. In the gamma band, the effect of the Notch filter is visible. Some other parameters were calculated and appended to the database in order to select the most suitable features for classification.

For each of these EEG signals, the Root Mean Square (RMS), maximum power spectrum, entropy, mean and autocorrelation values were calculated for each session to be used as features during the classification step being suitable for discriminating between different levels of cognitive load (Zarjam *et al.*, 2010).

Introduced by Shannon in information theory as a measure of a signal component distribution, entropy is a measure of signal impurity. In the analysis of EEG signals, many authors have used entropy to extract relevant features in general and, in particular, to working memory assessment (Phung *et al.*, 2014). A higher value of entropy indicates a more complex system, which makes it less predictable (Phung *et al.*, 2014).

Besides all this, autocorrelation is heavily used in time series analysis and forecasting, measuring a set of currently recorded values against a set of past recorded values to see if they correlate.

The creation of a database was necessary to easily store and analyse later the large volume of information corresponding to the calculated parameters for all users, EEG channels, and bands selected in this study. The database contains two tables: *Users* and *Results*. The *Users* table that stores personal information about users, namely name, age, gender, and user_id, is protected by administrative rights. The *Results* table contains the following fields (Fig. 6):

- user_id: user identifier;
- channel: the channel corresponding to the headset with which the test was performed (the electrode);
- signal_type: the type of frequency band used (Theta, Alpha, Beta, Gamma, Delta);
- test_type: the type of the performed test;
- mean: the calculated average value (AVG);
- rms: the calculated RMS value;
- entropy: the Shannon entropy value;
- autocorrelation;
- ps: the maximum value for the power spectrum.

user_id	channel	signal_type	test_type	mean	rms	entropy	autocorr	ps
1	p3	theta	2-back	-0.00023248	4.71302	32249.3	1947620	8492380000
1	p3	alpha	2-back	-0.00057253	8.87225	31820.2	6901970	19289200000
1	p3	beta	2-back	-0.00052682	5.7494	26967.7	2898350	8676050000
1	p3	gamma	2-back	-0.00000138	5.9107	-18724400	3063250	10470700000
1	p3	delta	2-back	0.00523088	9.58742	8232.06	8059520	113926000000
1	f3	theta	2-back	0.00016335	6.96734	30526.4	4256370	5130980000
1	f3	alpha	2-back	-0.00049454	8.82754	33394.6	6832580	17970400000
1	f3	beta	2-back	-0.00050803	5.55219	27045.8	2702930	7867560000
1	f3	gamma	2-back	0.00001019	5.6348	-1162690	2783960	9594900000
1	f3	delta	2-back	0.00541423	13.293	9815.19	15493500	97833900000
1	f4	theta	2-back	0.00020392	5.2423	33314.4	2409620	4281870000

Fig. 6 – Some selected columns and rows from Result table.

2.4. Feature Extraction and Classification

In the BCI systems, the supervised classification of EEG signals is intensively studied. Since the performance of the learning process is correlated with WM activity (Antonenko *et al.*, 2010), there are several methods for classifying EEG signals, namely radial basis function neural networks, decision trees, Bayesian networks, logistic regression, Markov models, Naïve Bayes (Deng *et al.*, 2015), ensemble techniques (bagging or boosting algorithm - AdaBoost or Random Forest (RF)), and so forth.

In this paper, the classification algorithms used to assess a person's WM load during different activities were: Support Vector Machine (SVM), K-Nearest Neighbors (kNN), and RF. Accordingly, there are 4 classes for WM assessment numbered based on the encoding of the test type with the number from the n-back representation (n = 1, 2, 3): the first one for 1-Back, the second one for 2-Back, the third one for 3-Back, and the fourth one for the Rest state, each class discriminating the working memory activity hence the cognitive load.

The SVM classifier offers a promising approach for classifying WM load levels, being resistant to process inconsistent data. SVM separates the classes by calculating a decision surface at the maximum distance from the classified points (Ahangi *et al.*, 2013). If the classes are not linearly separable, a minimum number of misclassified instances is ensured. The advantages of SVM are related to noise resistance and robustness when using large data sets. Since the limitation imposed by the linear separation problem is severe, SVM allows the use of kernel functions to transpose the problem from the initial instance space to the feature space, which ensures a linear solution of the space separation problem.

The kNN is a supervised learning algorithm based on the labeling value received from the nearest neighbors. They are consulted, and by a majority vote, the class of the new instance is decided (Ahangi *et al.*, 2013). However, since the identification of the nearest neighbors depends on the number of existing patterns in the dataset, the problem of choosing the closest neighbors is not an easy one. Various metrics have been studied and proposed for this purpose, each having its advantages. At the same time, the kNN algorithm becomes challenging when it needs to process a large number of instances.

The learning based on ensemble involves the aggregation of several weak classifiers to achieve a good result. Each of the weak classifiers manages to solve the classification problem independently, and, through mediation or by majority vote, the final affiliation to a certain class can be indicated (Ahangi *et al.*, 2013). The RF algorithm works with decision tree ensembles or regression. RF samples attribute without replacing them to build the nodes of each tree. Each tree associates a class with the patterns in the set, the forest decides the final class by majority vote or mediation. The RF algorithm offers accuracy in classification, and it is relatively robust in processing data containing noise, and relatively fast and straightforward to parallelize (Şen *et al.*, 2014).

In the experimental studies, the multiclass classifiers RF, kNN, and SVM were trained and tested to extract the essential features for the four levels of cognitive load mentioned above. For this purpose, 30% of the dataset was used for training, and the rest of 70% was used for testing. The results indicate the capacity of these features to discriminate between different CL levels and the accuracy and the confidence of the chosen classifiers to distinguish between the different activities performed by the WM. Each experiment employed several attributes, namely: the channel, the type of signal, AVG, RMS, entropy, autocorrelation, and ps.

For these attributes, some testing scenarios have been configured. Thus, in the first scenario Scenario1, the RF, SVM, kNN were trained and tested for the whole dataset, in the second one, Scenario2, RF, SVM, and kNN were used only for frontal channels involving Alpha and Beta frequency bands. In the third scenario, Scenario3, the same classifiers were used for frontal channels using Alpha, Beta, and Gamma frequency bands. For all these scenarios, the classifiers were trained using the same training set generated by randomly selecting a subset of samples from the database. The number of trees configured in RF was of 50 trees. An RBF kernel function was used for SVM, and a Jaccard metric was used for kNN classifiers with k = 5.

3. Results and Discussions

Four sighted volunteers (students) and eight VIPs took part to the n-back tasks performed with the proposed setup and software. The experiments conducted with sighted participants were important for adjusting the software resources, to increase the reliability of the proposed framework and to have a reference in this study. The developed framework proved its usefulness especially in terms of the Romanian audio stimuli and the possibility to choose the time per question and times to play. The last two parameters were carefully chosen to create the equilibrium between users' capacity to clearly distinguish and memorize the audio stimulus and the length of each test. Every trial was proceeded by rest test, during which the user must relax and tries not to think about anything.

It is worth emphasizing that in our experiments, we concluded that on the whole, the sighted people had obtained better results performing n-back tasks for visual stimuli compared to audio stimuli. Likewise, it must be underlined that using audio stimuli, the average of the scores obtained by VIPs, is significantly greater than that achieved by the sighted users. In line with this remark, the sample entropy (SamEn) was calculated for n-back tasks involving all volunteers. The SamEn was chosen because it is usually used for assessing the complexity of physiological time-series signals; it does not depend on data length and does not include self-matches (Delgado Bonal and Marshak, 2019). In our previous experiments, we have obtained reliable results as well (Ungureanu *et al.*, 2019). In Fig. 7, it can be seen similar variations of SamEn for VIPs, with a small growth during the trial and an average value of approximately 1.2. In the case of a subject with healthy sight, the SamEn presents considerable variations and oscillations reaching values above 2.

The obtained dataset was used to select the proper features for performed tasks and, in the end, to classify the EEG signals. The classification methods were applied in three scenarios.

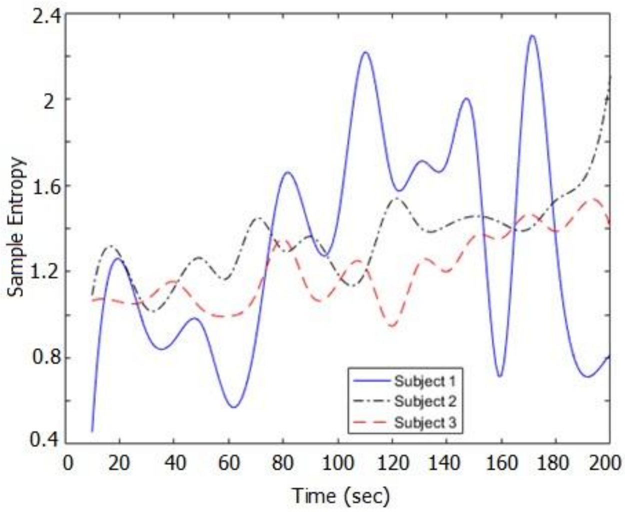

Fig. 7 – The sample entropy variation along a 2-back task for two VIPs (subject 2 and 3) as sighted person (subject1).

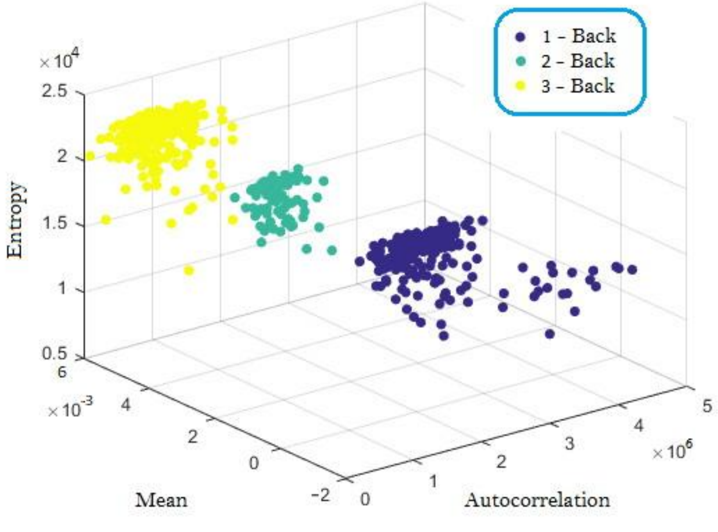

Fig. 8 – The n-Back classification in *scenario1*.

Scenario1: the ability of some classifiers to distinguish between working memory (cognitive load) levels was evaluated (Fig. 8). For the proposed experimental scenario, the mean values of the error rate and the areas under the curve (AUC) for all classifiers were recorded during more distinct runs on the same input data. The AUC indicator was chosen to evaluate the performance of the classifiers. Since AUC represents the probability that a positive event is classified as positive, a model characterized by AUC values greater than 0.9 reflects the accuracy of the algorithm. For the SVM and kNN algorithms, the values of the registered AUC indicator were in the range [0.997; 1], while for RF, its value was 1 for all test cases.

The ability to retain information or segments of information while solving a problem is done with the help of short-term memory. The use of the WM increases the activity of the brain in the frontal and prefrontal regions. During research on the activity of the human brain, it has been observed that the frontal lobes are generally associated with higher-level cognitive functions such as thinking, analyzing information or making decisions (Sound of Vision, 2020; Ungureanu *et al.*, 2017b). These reasons led us to introduce *Scenario2* and *Scenario3*.

Fig. 9 pictures the clear distinction between the levels of CL achieved for an user, mainly that the optimal selection of features has the decisive role of distinguishing between different stages of memory load. The gamma band provides valuable information for the process of classifying n-back activities since gamma waves are responsible for the formation of ideas, language, information processing in memory, being also associated with different types of learning (Cîmpanu *et al.*, 2017).

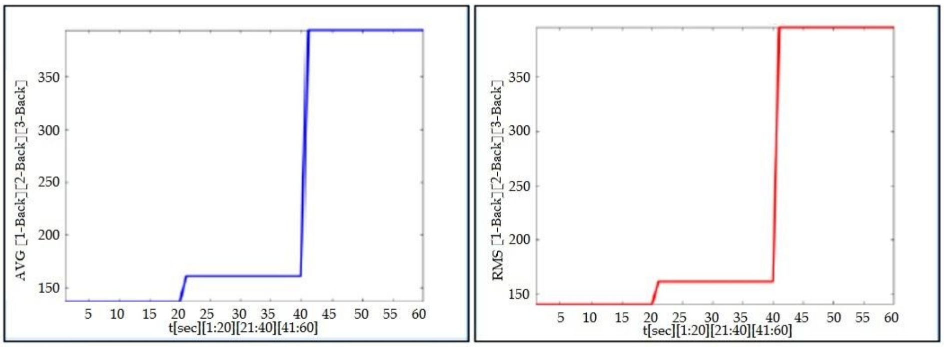

Fig. 9 – AVG and RMS indicators, calculated for EEG signals recorded during *n*-back memory tasks for *scenario3*.

In the second scenario, the classification accuracy rate was also high 98% for RF, respectively 88% for SVM and kNN, and increased when the Gamma wave is involved in the third scenario to 100% for RF, respectively 99% for SVM and kNN. The obtained results highlight the role of RF, kNN, and SVM classifiers when using several classes, to select the proper attributes necessary for effective EEG signals classification subject to the n-back paradigm. All classifiers performed accurately in EEG pattern classification applications. Still, the load level in the short-term memory can be identified with great accuracy using only signals collected mainly from the frontal region, with RF.

4. Conclusions

The purpose of the presented study was the design and implementation of a framework for working memory and cognitive load assessment for visually impaired persons involved in an audio n-back task as the first step in specific training process necessary for efficient use of sensory substitution devices. This application development was required in an extended study focused on assessing the cognitive and emotional activity of VIPs who use sensory substitution devices for navigation in different environments. The records from rest tests and n-back tasks were subsequently used as references in the comparative assessment of WM and CL of VIPs involved in training or navigation tasks. The users who did not speak English had difficulty completing the tests if the existing online applications were used and, some of them even gave up without wanting to resume experiments.

The n-back audio module, specially designed for Romanian speaking visually impaired subjects, is the main achievement of this study and represents the novelty of this research. The usability of this application had an essential role in conducting the experiments efficiently and in obtaining accurate signal datasets based on a good synchronization between stimuli and corresponding EEG signals. The module for feature extraction, classification and visualization focuses on algorithms dedicated to select suitable features for EEG signals and to classify the brain waves for evaluating WM and CL corresponding to the n-back paradigm. In further research, the correspondence between the difficulty levels of the n-back tasks and the complexities of the routes traversed by the VIPs guided by the SSD will be highlighted.

This study proves that a high-quality brain activity evaluation for VIPs is achieved if experiments are well-conducted, which means customized n-back tasks, top range EEG signal acquisition and specific software adapted for classification.

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EVALUAREA ACTIVITĂŢII MEMORIEI DE LUCRU A PERSOANELOR CU DEFICIENŢE DE VEDERE. STUDIU DE CAZ

(Rezumat)

În acest articol este prezentată arhitectura unei aplicaţii pentru evaluarea activităţii memorie de lucru pe termen scurt a persoanelor nevăzătoare sau cu deficienţe de vedere conform testelor de tip n-back. Datorită modului particular în care persoanele nevăzătoare percep stimuli ambientali, testele n-back standard nu sunt aplicabile şi prin urmare, a fost proiectată şi implementată o aplicaţie software adaptată să execute experimente n-back pentru diferiţi stimuli audio în engleză şi română. Activitatea memoriei de lucru şi evaluarea încărcării cognitive s-au bazat pe tehnici de interfaţă creier-calculator. Utilizând aplicaţia dezvoltată, au fost efectuate un număr semnificativ de teste cu voluntari, persoane cu vedere normală sau cu deficienţe de vedere şi s-a dezvoltat o bază de date ce conţine semnalele EEG achiziţionate în timpul experimentelor. Semnalele brute au fost procesate offline pentru a explora cele mai potrivite trăsături pentru evaluarea memoriei de lucru. Unii algoritmi de clasificare au fost aplicaţi pentru a discrimina nivelul încărcării cognitive iar rezultatele obţinute sunt conforme cu teoria si evidenţiază calitatea bună a setului de date experimental utilizat.