

Optimized Brain Computer Interface System for Unspoken Speech Recognition: Role of Wernicke Area

Nassib Abdallah, Pierre Chauvet, Abd El Salam Hajjar, Bassam Daya

Abstract—In this paper, we propose an optimized brain computer interface (BCI) system for unspoken speech recognition, based on the fact that the constructions of unspoken words rely strongly on the Wernicke area, situated in the temporal lobe. Our BCI system has four modules: (i) the EEG Acquisition module based on a non-invasive headset with 14 electrodes; (ii) the Preprocessing module to remove noise and artifacts, using the Common Average Reference method; (iii) the Features Extraction module, using Wavelet Packet Transform (WPT); (iv) the Classification module based on a one-hidden layer artificial neural network. The present study consists of comparing the recognition accuracy of 5 Arabic words, when using all the headset electrodes or only the 4 electrodes situated near the Wernicke area, as well as the selection effect of the subbands produced by the WPT module. After applying the artificial neural network on the produced database, we obtain, on the test dataset, an accuracy of 83.4% with all the electrodes and all the subbands of 8 levels of the WPT decomposition. However, by using only the 4 electrodes near Wernicke Area and the 6 middle subbands of the WPT, we obtain a high reduction of the dataset size, equal to approximately 19% of the total dataset, with 67.5% of accuracy rate. This reduction appears particularly important to improve the design of a low cost and simple to use BCI, trained for several words.

Keywords—Brain-computer interface, speech recognition, electroencephalography EEG, Wernicke area, artificial neural network.

I. INTRODUCTION

A Brain Computer Interface (BCI) is a direct connection between the human brain and exterior devices. It relies on systems that acquire signals directly from the brain, analyze them, and translate them into commands. BCIs are studied in numerous fields (medical, military, advertisements, gaming, etc.) and are linked nowadays with the internet of things [1].

Yet, BCIs targeting a medical issue are the focus of many researches, to improve the lives of persons affected by number of different disease [2]. In this paper, we propose a BCI system for people with speaking issues, focused on the signals acquired from the brain using the Electroencephalography technique (EEG). In fact, the EEG is widely used in this field of research, as it is noninvasive and provides high temporal resolution of the acquired signal, for a low cost and portable material [3]. More precisely, we investigate the importance of the Wernicke-Broca zone for the recognition of 5 Arabic

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unspoken words, compared to results obtained during the acquisition of all the channels around the scalp of a human subject.

This article discusses the impact of EEG sensor selection in the Wernicke area, by comparing the results obtained when all the recording channels used in the acquisition process are retained. Thus, we investigate the dataset reduction using the selection of the Wernicke EEG sensors, and other methodologies like dimension reduction, in order to increase the speed of our system, by selecting the essential information of the recorded signals.

The best result provided by our system for the recognition of five unspoken speech words was 76.2% of accuracy in the classification process (Table IV). This result was according to the testing dataset injected into the system, based on artificial neural network model, to validate its output decision. Although, this work discussed the impact of selecting subspaces from the decomposition result, applied after the implementation of the Wavelet Packet Transform. Indeed, it gives 67.5% of recognition, providing a high reduction in the dataset dimension (Table VII).

In the first section of this paper, we present a state of art of the Brain computer Interface and the unspoken speech related works. The second section presents the system architecture for the recognition of 5 Arabic words {light, turn out, eat, drink and sleep} as shows Table I.

In the third section, we present and discuss the results of our system accuracy, through the comparison of different methodologies and parameters like the selection of subspaces, the set of features, etc. Finally, we conclude this paper with a conclusion and perspectives.

TABLE I
5 ARABIC WORDS WITH ENGLISH TRANSLATION AND PRONUNCIATION

Words in English	Words in Arabic	Pronunciation
Eat	أكل	AKALA
Drink	شرب	SHARAB
Sleep	نام	NAMA
light	أضيء	ADAA
Turn out	أطفئ	ATFAA

II. STATE OF ART

The human brain consists of 6 different lobes (Frontal, Parietal, Occipital, Temporal, Limbic and Insular cortex) [4]. The first four lobes represents the main lobes positioned as shown on Fig. 1.

TABLE II
RECOGNITION RATE FOR 3 LEVELS OF DECOMPOSITION USING THE FIRST SET OF FEATURES

	Channel selection	Accuracy (%)	F-measure C1 (%)	F-measure C2 (%)	F-measure C3 (%)	F-measure C4 (%)	F-measure C5 (%)
Training	All Channels	58.6	62.58	54.36	53.42	55.61	60.49
	Wernickes	72.5	83.02	56.52	56.52	53.7	56.53
Test	All Channels	57	61.14	49.65	49.65	54.25	59.29
	Wernickes	68.5	76.5	70.34	60.02	53.85	62.37

TABLE III
RECOGNITION RATE FOR 8 LEVELS OF DECOMPOSITION USING THE FIRST SET OF FEATURES

	Channel selection	Accuracy (%)	F-measure C1 (%)	F-measure C2 (%)	F-measure C3 (%)	F-measure C4 (%)	F-measure C5 (%)
Training	All Channels	64.6	65.95	66.22	71.58	35.63	58.94
	Wernickes	81.5	86.9	86.62	75.99	71.06	68.2
Test	All Channels	62.6	63.55	63.75	73.01	29.72	54.59
	Wernickes	74.2	83.68	77.03	65.49	59.48	59.45

TABLE IV
RECOGNITION RATE FOR 8 LEVELS OF DECOMPOSITION USING THE SECOND SET OF FEATURES

	Channel selection	Accuracy (%)	F-measure C1 (%)	F-measure C2 (%)	F-measure C3 (%)	F-measure C4 (%)	F-measure C5 (%)
Training	All Channels	85.2%	88.4%	87.97%	83.74%	82.33%	75.21%
	Wernickes	85.8%	91.08%	90.21%	75.88%	78.84%	77.84%
Test	All Channels	83.4%	87.95%	85.57%	82.64%	80.13%	69.26%
	Wernickes	76.2%	85.4%	83.48%	60.55%	72.49%	52.47%

TABLE V
RECOGNITION RATE FOR 8 LEVELS OF DECOMPOSITION USING THE SECOND SET OF FEATURES AND THE SELECTION OF THE FIRST FOUR DETAILS COEFFICIENTS OF THE FIRST FOUR SUBSPACES CD1, CD2, CD3 AND CD4

	Channel selection	Accuracy (%)	F-measure C1 (%)	F-measure C2 (%)	F-measure C3 (%)	F-measure C4 (%)	F-measure C5 (%)
Training	All Channels	58.6	62.58	54.36	53.42	55.61	60.49
	Wernickes	72.5	83.02	56.52	56.52	53.7	56.53
Test	All Channels	57	61.14	49.65	49.65	54.25	59.29
	Wernickes	68.5	76.5	70.34	60.02	53.85	62.37

TABLE VI
RECOGNITION RATE FOR 8 LEVELS OF DECOMPOSITION USING THE SECOND SET OF FEATURES AND THE SELECTION OF THE LAST FOUR DETAILS COEFFICIENTS OF THE LAST FOUR SUBSPACES CD5, CD6, CD7 AND CD8

	Channel selection	Accuracy (%)	F-measure C1 (%)	F-measure C2 (%)	F-measure C3 (%)	F-measure C4 (%)	F-measure C5 (%)
Training	All Channels	37.8	49.92	18.08	23.45	30.81	33.88
	Wernickes	42.2	52.1	40.88	10.42	31.07	48.6
Test	All Channels	33.4	47.75	9.15	18.43	25.5	23.46
	Wernickes	28.4	42.73	19.15	3.73	7.77	16.63

TABLE VII
RECOGNITION RATE FOR 8 LEVELS OF DECOMPOSITION USING THE SECOND SET OF FEATURES AND THE SELECTION OF THE DETAILS COEFFICIENTS OF THE MIDDLE SUBSPACES CD2, CD3, CD4, CD5, CD6 AND CD7

	Channel selection	Accuracy (%)	F-measure C1 (%)	F-measure C2 (%)	F-measure C3 (%)	F-measure C4 (%)	F-measure C5 (%)
Training	All Channels	74.4	77.9	76.77	72.5	73.47	63.76
	Wernickes	79	81.75	80.64	78.74	79.9	67.62
Test	All Channels	69.7	73.56	71.61	70.13	66.69	54.31
	Wernickes	67.5	72.48	70.21	66.03	57.11	64.34

The frontal lobe constitutes two thirds of the human brain. It is the main lobe where the personality of the human is formed. Yet, the frontal lobe is used to make voluntary movements such as walking, eating or drinking. In addition this lobe is necessary to speak meaningfully [5].

The parietal lobe contains a map of neurons that have an

important role to process the sensory information from various parts of the body and specifically the body's five senses such as the sense of touch, smell, audition, taste and visual information to guide the movement of the body [6].

The occipital lobe is located at the back of the brain as shown in Fig. 1. It is the smallest of the four main lobes and is

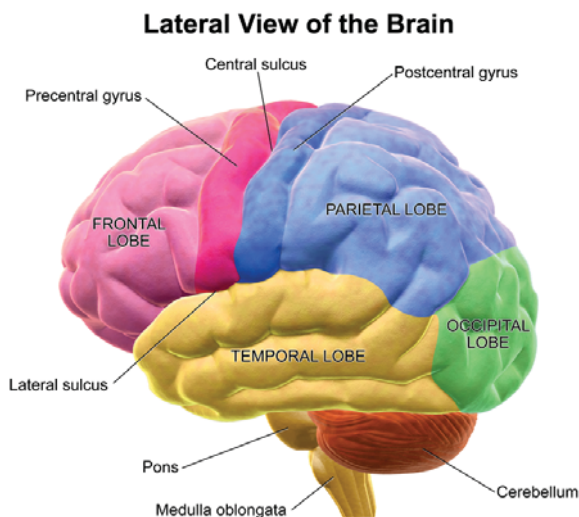


Fig. 1 Lateral surface of cerebrum

mainly responsible of visual perception and color recognition. In fact, it processes the data acquired from the eyes and links the information acquired with images in the memory of the subject [7].

The temporal lobe is located in proximity of the ears: there is one temporal lobe at each side of the brain. It plays an important role in the processing of sensory inputs, as it is involved in the storage of information in the memory of the subject. Also, it contains the auditory and language processing, with the speech production and comprehension localized in the Wernickes area [8]. In fact, the process of the construction of unspoken words in the brain is mainly relied to the Wernickes and Broca area. The information is processed in the Wernickes area and then send to the Broca area through the Arcuate Fasciculus, a set of axons that connect different areas of the brains for the language use. The Broca area receives the information and send commands to the muscular cortex to produce the articulation for the constructed word.

The BCI targeting people having speaking issue have to consider the facts mentioned above. As this paper aims on a system for automatic recognition of unspoken words, we can improve it taking into account from where the problem is located in the brain, using the good areas during the recordings of the EEG.

The construction of a BCI consists of four main phases or modules [3]: (i) The EEGs acquisition. (ii) The preprocessing of the acquired signals to enhance their qualities and remove the noise. (iii) The feature extraction to extract relevant features from these signals (iv) And finally the classification, in order to associate the feature vector to different known classes.

Several BCI systems were constructed targeting unspoken speech based on the Electroencephalographic technique for the recognition of unspoken words. There were two BCIs targeting the recognition of unspoken words were (Calliess et al., 2006) [9] worked on a system for the recognition of the five words spelling the NATO alphabet Alpha, Bravo, Charlie, Delta, Echo using the system 10-20 for the acquisition of the brain signals. They obtain 49% of classification using 16

recording channels. Yet, the work done by (Porbadnigk et al., 2008)[10] using the same material of recording as Calliess for the same set of words using german subjects obtained 45.5% of classification of the five english words Echo,Charlie,Beta, Delta, Alpha. However, the work done by (Salama et al., 2014) [11] on a system for the recognition of two english words using the Neurosky MindWave Headset containing only one recording EEG electrode gave 56% of classification for the two english words YES, NO.

III. SYSTEM ARCHITECTURE

Fig. 2 shows the architecture of the proposed BCI system for unspoken speech recognition, based on the fact that the constructions of unspoken words rely strongly on the Wernicke area, situated in the temporal lobe. This system is composed of four main components that are: Data Acquisition, Data Preprocessing, Feature Extraction, and Data Classification. The Data Acquisition allows treating the EEG signals, reached from the scalp of the subject, and extracting the pertinent EEG according to the user choice. However, the user can choose to extract only the Wernicke channels or extracting all the 14 channels. These extracted signals will be followed by a vector Marker called M; it contains the index of the start and the end of each window in the EEG Signal. This output will be injected into the second component "Data Preprocessing" that allows applying the Common Average Reference algorithms, and splitting the EEG signal, that represent a session of 1min 30seconds of recording, according to the marker vector representing the parameter 'M' in our system. The Feature Extraction allows implementing the Wavelet Packet Transform Algorithm, this component has three parameters in addition to the matrix of preprocessed signals; the first parameter 'L' specify the number of decomposition level, which was applied on the original signal by the WPT Algorithm; the second parameter 'Ftv' specify the choice of the features set, computed on the computed coefficient vector resulting from the WPT decomposition; and the third parameters specify the band of ID for the selected subspaces resulting from the WPT decomposition, in order to reduce the dimension of the dataset. The Feature Extraction outputs are features vectors that will be injected into an artificial neural network, based on three layers in the Fourth and final component called "Data Classification", this component aims to classify the input data into five different classes through a configured neural network. It takes one parameter 'NbH' which specify the number of hidden neuron in the hidden layer of the neural network.

A. Data Acquisition

This module is the first phase of the construction of a Brain Computer Interface. It consists of recording the brain wave through specific materials of acquisition. Yet, there are two different categories of acquisition of the brain signal. The first represents the invasive techniques which give high resolution and efficient signals. However, the disadvantage of this category is its need to a surgery which can be very harmful and dangerous for the subject [3]. The second category concerns noninvasive techniques, that are the most used in

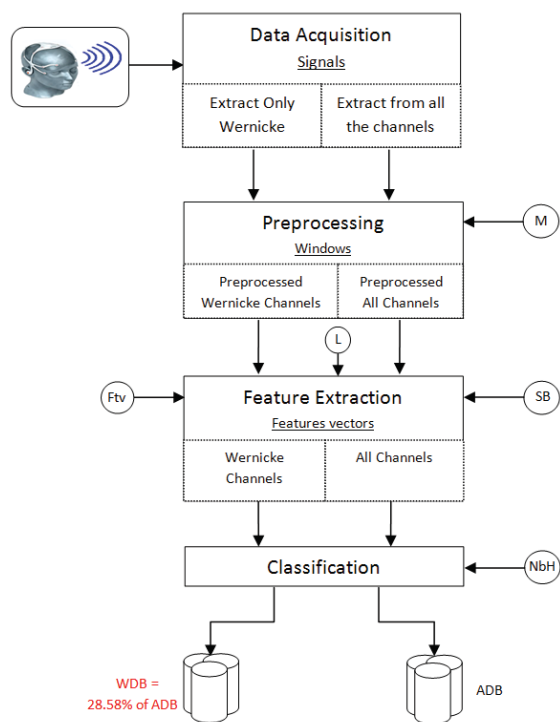


Fig. 2 General architecture of the Optimized BCI system

the BCI researches since they are simpler to implement and harmless for the subject. The noninvasive techniques consist of recording the brain signals, through harmless methods like fixing electrodes on the scalp of a subject to record the electric flow from the brain (Electroencephalography), recording the magnetic flow (Magnetoencephalography), using the Blood Oxygenation Level Dependent (BOLD) or other methods [3]. In this paper, the electric flow was recorded and analyzed by fixing an Emotiv Epoc+ headset on the scalp of a subject, using the EEG technique for the acquisition of the data (Fig. 4). The Emotiv Epoc+ is a headset containing 14 bio potential sensors covering most of the scalp of a subject (Fig. 5). It sends the recorded EEG through a USB transceiver. The data are then saved and visualized through the Emotiv APK called Testbench. The recording was realized on subjects having between 19 and 25 years old. Each subject performs between 3 and 5 sessions of recording for each of the 5 arabic words. Each session consists of 1m30sec of recordings with 15 and 20 repetition of a same word. The session consists of a video made specifically for each word as shows Fig. 3, where Mi represents a marker injected manually during the acquisition to separate each windows (begin and end of the though word), Ri represents the repetition of a though word, and n is the number of repetition in each session.

The records are saved in EDF format files where each file represents a session for a specified subject and a specified thought word. Each EDF file contains a row for each EEG channel, i.e. the recorded values for each of the 14 electrodes AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4, and a row for the marker values injected during the acquisition process.

Only F7, FC5, T7 and P7 electrodes, representing the sensors nearby the Wernickes area for right handed subjects, were selected to compare the recognition of the 5 words with the classification obtained by selecting all the 14 EEG sensors of the Emotiv Headset. By selecting only 4 of the 14 channels, the size of the database is reduced to 28.57% of the original database according to the formula:

$$reduction = \frac{Number\ of\ selected\ channels * 100}{Total\ number\ of\ channels}$$

B. Preprocessing

This phase consists of removing artifact and noise in order to increase the rate of recognition. However, there are many methods which can be implemented to enhance the quality of the recorded signals, like Common Average Reference (CAR) which remove the common components between all the recording channels, Principle Component Analysis (PCA) which can be either using for the preprocessing and for the Feature extraction/dimension reduction, Adaptive Filters which remove the noise through a set of filters adapted to remove specific band of frequencies from the signals and other techniques [3]. In this work we have implemented the Common Average Reference which is particularly performant in removing artifacts like potentials induced by muscular/cardiac contractions. This method is applied on each recording electrode to eliminate the common components between all the channels: it consists of computing a mean vector of the recorded channels and subtracting this mean vector from each channel.

C. Feature Extraction

This phase consists of extracting relevant characteristics from the EEG signals in order to construct a feature vector representing the essential data of the recorded signal. For that, the most used method applied is the Wavelet Packet Transform since it is efficient for non stationary signals which is the case of EEG signals. However, Principle Component Analysis and Independent Component Analysis can be applied to extract principle components or independent components from the signals [3]. The use of feature extraction methods is related to the specificities of the processed signals. The process to extract features from the signal in the proposed system follows the steps below.

First, the preprocessed signals were imported and injected into the feature extraction module, which consists of the Wavelet Packet Transform with three or eight levels of decomposition. The results for a three level decomposition is 4 subspaces containing 3 vectors of details coefficients and a vector of approximation coefficient. On each vector of coefficient for each subspace, 2 sets of features were computed:

- 1) Variance, Standard deviation, Energy, Waveform length
- 2) Variance, Entropy, Energy, Waveform length

The results of this process is, for each EEG channel, a vector of characteristics containing 16 values for three levels of

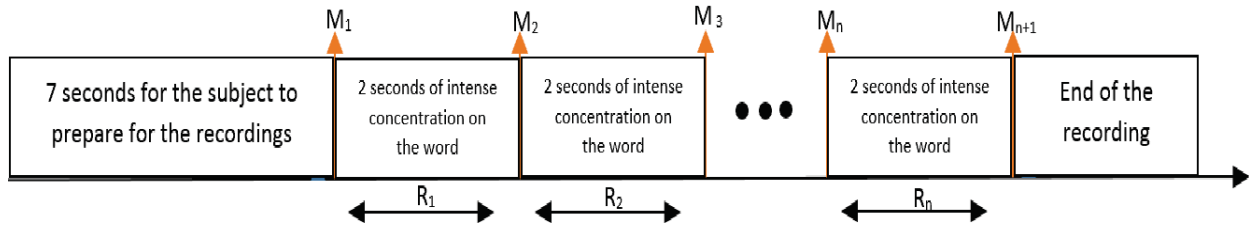


Fig. 3 Video Procedure



(a) Headset on the scalp of a subject (b) Picture taken during the acquisition process

Fig. 4 Acquisition process



Fig. 5 Emotiv epoc+ EEG Sensors, 14 EEG sensors (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4), 2 references (CMS and DRL)

decomposition and 36 values for eight decomposition. The number of values is related to the number of subspace created after the decomposition of the Wavelet Packet Transform, following the formula below:

$$FeatureVectorValues = (Level+1) * NumberOfFeatures.$$

D. Classification

The Classification is the fourth module of the BCI system. Since the feature vectors are built in the third phase, these vectors are injected in a machine learning based classifier. There are two main categories of classifier. The first consists of linear classifier like Linear Discriminant Analysis and Support Vector Machine which classify the data using hyperplanes. The second category consists of non linear classifier like Random forest based on tree decision, K nearest neighbor, Artificial neural network and others [3]. In this work, we implement an Artificial Neural network since it is robust and is efficient tool

for classification and pattern recognition [12]. After the feature extraction phase, a part of the data of interest was selected from the dataset and was splitted into two subsets: 80%, 20%. The first subset was injected in a one hidden-layer neural network as a 2D matrix and followed by a 1D target vector representing the target classes identifier of each observation injected in the input. This process allows the neural network to train and adapt his weights to give an output similar to the target matrix through the minimization of a least-square problem. The second 20% of the dataset was used for testing the output of the trained neural network.

The results shown in Tables I-VI are measures of the accuracy of the classification and the F-measure, which is related to the recall and precision formulas:

$$Recall = \frac{TruePositives}{FalseNegatives}$$

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives}$$

$$F_measure = 2 * \frac{Recall * Precision}{Recall + Precision}$$

IV. RESULTS AND DISCUSSION

The main result of this work is an optimized BCI system for unspoken speech recognition. In this section, we will present and discuss the performance results of the system according to several parameters such as: level of decomposition, Feature selection, and subband selection.

A. Levels of Decomposition

The first comparison between results was done by modifying the number of decomposition in the Wavelet Packet Transform algorithm. As shows Table II, the results obtained for 3 levels of decomposition by selecting the EEG sensors in the Wernickes area shows a rate of recognition higher than the recognition obtained by selecting all the 14 EEG sensors. However, the use of eight levels of decomposition gave even better results using only the 4 sensors near the Wernicke area (as shows Table III) with an average accuracy of 81.5% on the training dataset and 74.2% on the test dataset, for the classification of the 5 Arabic words. In the rest of this document accuracies are given in this order: training set - test set.

B. Features Selection

The second comparison criteria is the selection of the set of features computed on the coefficients vectors. The first set of features (Variance, Standard deviation, Energy and Waveform length) gave the results obtained in Table III. The computation of the Entropy instead of standard deviation provides (as shows Table IV) an accuracy of 85.8%-76.2% , which validate that the entropy is a better relevant feature to extract information from the signal.

C. Subband Selection

In order to reduce the size of the dataset to analyze, we selected some subspaces given by the WPT decomposition process. Thus, the results given by Table IV were the best results obtained. the sub-band selection component was applied on the system with 8 levels of decomposition and the second set of characteristics (Variance, Entropy, Waveform Length and Energy).

1) *CD1..CD4*: As shows Table V, the selection of the first 4 subspaces gives a reduction of

$$100 - \frac{4 * 100}{L} = 55.55\%$$

With L= Number of Levels+1 = 9.

Yet, this process gives (As shows Table V) an accuracy of 72.5%-68.5% by only selecting the Wernicke area.

2) *CD5..CD8*: However, the results were not good when the subspaces CD5, CD6, CD7 and CD8 were selected, with an accuracy of 42.2%-28.4% as shows Table VI.

3) *CD2..CD7*: Since the results shown in Table V are better than the results using CD5 through CD8 subspaces, the middle subspaces (CD2, CD3, CD4, CD5, CD6 and CD7) were selected in order to detect where the essential information is localized. This gives a reduction of 33.33% of the original dataset according to the formula:

$$reduction = 100 - \frac{Number\ Of\ Selected\ Subbands * 100}{Total\ Number\ Of\ Subbands}$$

We obtain an accuracy of 79%-67.5% (As shows Table VII). The results provided by this selection allow us to conclude that a high amount of the essential information is in CD2 through CD7 subspaces.

V. CONCLUSION

This paper highlights the importance of the Wernicke area for the recognition of unspoken speech through a BCI. The proposed system, based on EEG analysis, consists of four main components. The first one is the headset allowing the acquisition of the EEG signal, done here through an Emotiv Epoc+ Headset. The second component is the preprocessing module apply to the recorded signals. We have implemented for that the Common Average Reference algorithm. The third component is the feature extraction module, where the Wavelet Packet Transform (WPT) is implemented to decompose the preprocessed signal into subspaces and give coefficient details used for the computation of two set of features. Finally, the fourth component is the classification module done by

configuring an Artificial Neural Network with 3 layers to classify the feature vector resulting from the third component. The test was done using as parameters the number of levels of decomposition of the signals and the set of features computed on the subband resulting from the decomposition process. In fact, the selection of only the EEG sensor on the Wernicke area gives the results shown in Tables II-IV. This confirms that the Wernickes area contains the semantic of the unspoken speech. Other tests were done on the dimensions reduction of the dataset. However, the number of levels of decomposition for the WPT method was taken into consideration as first criteria of amelioration of the quality of the BCI recognition. The second criteria was the type of features computed on the vectors resulting from the WPT decomposition. The third criteria was the comparison between the results obtained by selecting only the four Wernickes nearby sensor or all the 14 recording channels provided by the headset. The acquired methodology for the construction of our system, shows better results of classification than the BCI done previously targeting the recognition of 5 words, were it gives 79%-69.7% of recognition (Table VII) with only 28.57% of the original dataset, and add a reduction of 33.33% after selecting the sub-bands. This gives us a total reduction of 81% of the data set. Since we use only 19% of the original data set, we will afford a small loss of classification rate, although the accuracy obtained is higher than the last BCI constructed for the recognition of 5 words. Finally, The results conclude that the 4 sensors F7, FC5, T7 and P7 of the Emotiv epoc+ are indeed highly recommended for the construction of a Brain Computer Interface system for the recognition of unspoken speech, since they contains the highest quantity of the needed information. As perspective, the 3D printing of a headset containing only these 4 electrodes on the Wernickes area can gives a high rate of recognition of unspoken speech with a reduced price of the Headset and a greater ease of use.

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