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An Emotional Model based on Wavelet Coherence Analysis of EEG Recordings

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Abstract – Molding emotion from electroencephalography (EEG) recordings has been always a challenge to researchers. They have developed some models by analyzing the temporal and/or spectral properties of EEG recording. However, analyzing the temporal and spectral synchronization between two EEG recordings can provide information about the functional connectivity of the brain undetectable by the conventional methods. This paper presents a wavelet coherence analysis of EEG recordings acquired from healthy subjects while they are listening to verses from the Quran recited by different reciters. The results showed that the connectivity between some pairwise electrodes changes significantly with the emotion reported by the subjects. Therefore, they can be used as a model to estimate the emotion.

Index Terms – Auditory Stimuli, Brain Computer Interface (BCI), Electroencephalography (EEG), Emotion, Emotiv EPOC Neuroheadset, Functional Connectivity, Wavelet Coherence.

NOMENCLATURE

Brain Computer Interface – BCI, Coherence Slope – CS, Continuous Wavelet Transform – CWT, Cross-Wavelet Transform – XWT, Discrete Wavelet Transform – DWT, Electroencephalogram – EEG, Fast Fourier Transform – FFT, Frequency Averaged Wavelet Coherence – FA, Kernel Density Estimation – KDE, Power Spectral Density – PSD, Wavelet Coherence – WC, Wavelet Transform – WT

1.0 INTRODUCTION

Emotion plays an important role in our thinking and behavior and therefore understanding and estimating emotion can improve the communication between humans, from one side, and between humans and machines, from another side. Emotion can be recognized from external body's signals such as text, facial expressions, speech, body's gestures, or a combination of several signals [1-5]. Recently, body's internal signals are used to discriminate between emotions such as heart rate and brainwaves [6-7].Emotion's recognition has many applications in different domains such as education, heath, commerce, games, security, and many others [8-15]. However, the most important application for the computer scientists could be the natural language processing domain where the machine can understand the emotion of the user and react upon this understanding [16-17].

Recognizing emotion from brainwaves is based on identifying distinct EEG patterns associated with different emotions. It is usually done by analyzing the EEG recordings in time domain, frequency domain, or both. Correlation functions are used in time domain to identify similarities between segments from one recording or between two recordings [18]. Frequency domain reveals information that is invisible in time domain. Fast Fourier transform (FFT) is used to convert the recordings from the time domain to the frequency domain. Then the power spectral densities (PSDs) of the converted signal are calculated in several frequency bands and compared to find any possible association with the studied phenomena [19]. Other methods were proposed to estimate the power spectral densities (PSDs) such as the kernel density estimation (KDE) method [20].

Recently, wavelet transform (WT), both continuous wavelet transform (CWT) and discrete wavelet transform (DWT), was successfully used in many applications to find the oscillation in signals in time-frequency domain [21-23]. FFT and WT are similar transforms in the sense that they both measure the similarity between a signal and an analyzing function, however, they differ in their choice of analyzing function.

While the wavelet transform (WT) develops a time series into a time-frequency space, cross wavelet transform (XWT) can be used to find regions in time-frequency space where the two time series show high common power. Moreover, the wavelet coherence (WC) can be used to find regions in time frequency space where the two time series co-vary, but does not necessarily have a high power [24-25].

In this paper, the wavelet coherence (WC) is computed for selected pairs of the adjacent EEG recordings acquired from healthy subjects while they are listening to verses from the Quran recited by different reciters. The results showed that some pairwise recordings have high covariance values, while others have low covariance values. Using these covariance values, a connectivity map of the brain can be produced. The connectivity map showed the regions in the brain that are correlated with the emotion. Furthermore, the results showed that the covariance values of some adjacent pairwise recordings vary approximately linearly with the emotion. The slope of the approximated linear map, called the coherence slope (CS), is computed by fitting a first-degree polynomial function to the covariance values. This approximated linear map is considered as an emotional model that can be used to estimate the emotion from the covariance values of selected pairwise electrodes.

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2.0 METHODOLOGY

The process of building the proposed emotional model passes through two phases, the data collection phase, and the data analyzing phase. The data collection phase is an online phase where a designed experiment is run and the EEG data is recorded. The data-analyzing phase is an offline phase where a first-degree polynomial function is fitted to the data. These steps are explained in detail in the following subsections.

2.1 The Subjects

Seventeen male volunteers with age in the range 16 years to 45 years participated in the experiment. Participants were from different nationalities and had no past psychiatric or neurological disease. They also have no experience in brain computer interface (BCI) experiment. They have to sign an informed consent prepared in accordance with the regulation of the local ethic committee.

2.2The Stimuli

Seventy-Five verses recited by five different reciters were selected by experts based on the meaning of these verses. They expect that they could evoke different emotions. Ten seconds of a blank is added to the beginning of each verse to be used as a baseline for the recorded data.

2.3EEG Recording

EEG recording passes through three units, signal acquisition unit, importer unit and recording unit. The signal acquisition unit used in the proposed system is the Emotiv EPOC neuroheadset shown in Fig.1. The properties of theEmotiv EPOCare given in Table 1. The acquired signals are aligned, band-pass filtered, and digitized at frequency 128 Hz and wirelessly transmitted to a windows PC [26]. The importer unit is a Matlab®-based server that streams EEG signals acquired by the Emotiv headset to a Simulink® model in real-time [27]. The imported signal is recorded from inside Matlab® using a dedicated function [28].

Figure 1: The recording device (Emotivneuroheadset)

2.4The Experiment

The experiment starts with a pre-session, where the subject is informed about the experiment and the steps to follow in order to complete the experiment successfully; then consent is signed by the subject. The experiment is performed in a calm room with low lighting and comfortable ambient. The subject sits on an armchair in front of a PC. The Emotiv headset is mounted on the subject's head and the data acquisition program starts on the PC.

Table 1: Properties of the Emotiv EPOC

Number of channels	14 (plus CMS/DRL references, P3/P4 locations)
Channel names (International 10-20 locations)	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4
Sampling method	Sequential sampling. Single ADC
Sampling rate	128 SPS (2048 Hz internal)
Resolution	14 bits 1 LSB = 0.51μV (16 bit ADC, 2 bits instrumental noise floor discarded)
Bandwidth	0.2 - 45Hz, digital notch filters at 50Hz and 60Hz
Filtering	Built in digital 5th order Sinc filter
Dynamic range (input referred)	8400μV (pp)
Coupling mode	AC coupled
Connectivity	Proprietary wireless, 2.4GHz band
Power	LiPoly
Battery life (typical)	12 hours
Impedance Measurement	Real-time contact quality using patented system

After ensuring that the Emotiv electrodes are well connected with the program, the subject selects a verse and starts listing to it while he is focusing on the meaning of it. After each recording, the subject reports his emotion using on a scale between 0 and 100 where 0 means completely unhappy and 100 means completely. The experiment procedure is shown in Fig. 2.

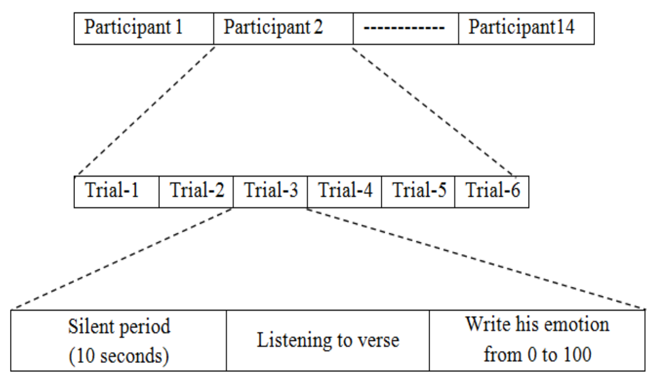

Figure 2: Procedure of the experiment

2.5Data Pre-Processing

The raw EEG signal is typically quite noisy; therefore, it is necessary to clean it up. To this end, a Butterworth bandpass filter of order eight in the band 2 to 42 Hz is used. Then, the average of all channels is used to references the filtered EEG signals by subtracting it from each channel. The last step is removing a baseline of the EEG signal from each channel for all recordings.

2.6 Pairwise Recordings

In this work, the EEG data are recorded from fourteen electrodes in the 10-20 International System as shown in Fig. 3. As the instant wavelet coherence (WC) is considered in this study, only the local electrode pairs in the frontal lobe are selected to avoid errors resulted from the propagation delays and the other electrical effects. Local electrodes pairs are defined as neighbor electrodes on the scalp. Each electrode has 3 to 6 adjacent electrodes as shown in Table 2.

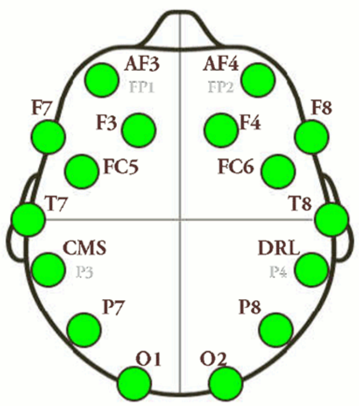

Figure 3: Fourteen electroencephalogram (EEG) electrodes in theEmotivneuroheadset

Table 2: Selected Adjacent Electrodes

Elect-rode	Adj. 1	Adj. 2	Adj. 3	Adj. 4	Adj. 5	Adj. 6
AF3	AF4	F3	F4	F7	FC5	
AF4	AF3	F3	F4	F8	FC6	
F3	AF3	AF4	F4	F7	FC5	FC6
F4	AF3	AF4	F3	F8	FC5	FC6
F7	AF3	F3	FC5			
F8	AF4	F4	FC6			
FC5	AF3	F3	F4	F7		
FC6	AF4	F3	F4	F8		

2.7 Wavelet Coherence

EEG recordings are nonstationary time series, which means that their frequency content changes over the time. In order to detect their common time localized oscillations, it is necessary to measure their coherence in the time-frequency domain. Wavelet coherence is an appropriate tool for this purpose and it will be used in this study. The computing formula of the wavelet coherence (WC) can be found in [24-25].

2.8Proposed Emotional Model

Consider two time series *x(t)*and *y(t)* coming from two adjacent electrodes and assume that their wavelet coherence is $WC_{xy}(t,f)$. Then, their coherence slope CS_{xy} is the slope of the line fitting the frequencyaveraged wavelet coherence $FA_{xy}(t)$defined as:

$$FA_{xy}(t) = \frac{1}{f_2 - f_1} \int_{f_1}^{f_2} WC_{xy}(t,f)\,df \quad (1)$$

wheref_1 and f_2 are the lower and upper frequencies of $WC_{xy}(t,f)$. Therefore, the relationship between the emotion and the frequency averaged wavelet coherence $FA_{xy}(t)$can be approximated by the following linear map:

$$FA_{am}(k) = CS_m Emotion(k) + c \quad (2)$$

Where$CS_m$is the maximum coherence slope between all pairs of selected adjacent electrodes (see Table 2), FA_{am} is the time average of $FA_{xy}(t)$ for the pair with maximum coherence slope, and *c* is a constant.

3.0 RESULTS AND DISCUSSION

Fig. 4 shows the verses and the reciters selected by the 14 subjects performed the experiment (the blue and green circles respectively). It also shows the emotion reported by the subject after each experiment (the red circles).From Fig. 4, one can see that the same verses recited by the same reciter produce different emotions for different subjects. For example, verse no. 1 from reciter no. 6 produces emotion 50 for subject 1 and 80 for subject 5.

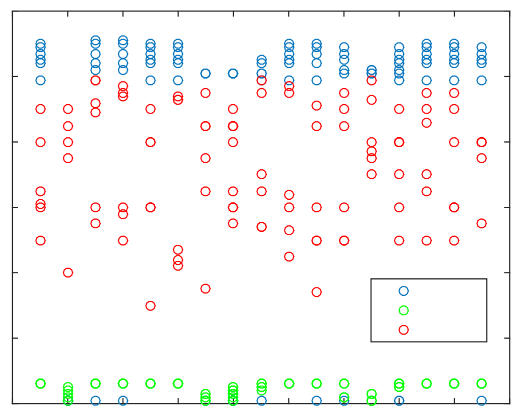

Figure 4: Experiment data

Fig. 5 shows a segment of the EEG recordings from one subject acquired from the14 Emotiv headset electrodes during the execution of the experiment.

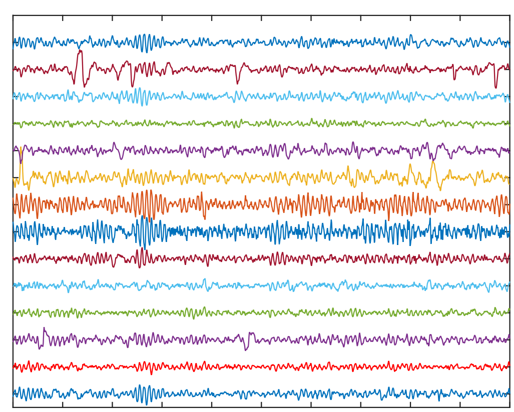

Figure 5: Segment of EEG recordings from a subject

Wavelet coherence is computed for each selected pair of adjacent electrodes according to Table 2 and for each subject [29]. Fig. 6 shows the wavelet coherence of the pair AF3-F7 from the EEG recordings of one subject. In Fig. 6, the horizontal axis shows the time while the vertical axis shows the frequency (the lower the frequency, the higher the scale).

Yellow regions in time-frequency domain represent significant interrelation between the two recordings. The arrows show lead/lag phase relations between the two recordings. When the two recordings move in the same direction, they are in phase and the arrows point to the right. When they move in the opposite direction, they are in anti-phase and the arrows point to the left. Arrows pointing to the right-down or left-up indicate that the first recording is leading, while arrows pointing to the right-up or left-down show that the second recording is leading [29].

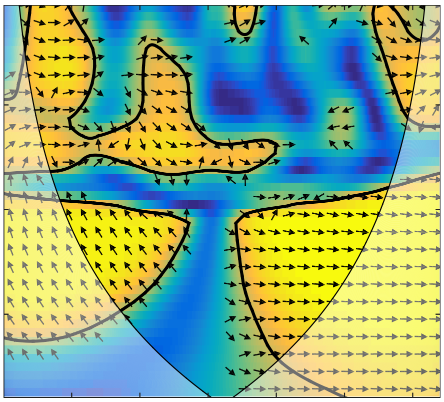

Figure 6: Wavelet coherence (WC) of AF3-F7 from the EEG recordings shown in Fig. 5

The wavelet coherence for each pair of adjacent electrodes and for each subject is averaged over the frequency domain to the get a new time series called FAxy time series. Fig. 7 shows a sample of these FAxy time series. For the time seriesFAxy obtained from the same pair of electrodes and from all subjects, a linear polynomial function is fitted to its averaged values over the time.

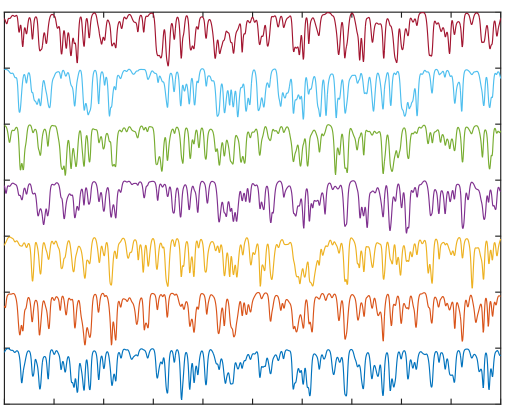

Figure 7: Frequency averaged wavelet coherence (FA_{xy}) of some EEG recordings

Fig. 8 shows the values of an averaged FAxy time series and a linear polynomial fitted function to the values.The slope of the fitted linear function is calculated for each of considered averaged FAxy time series. Table 3 shows these slopes (CSs) for all considered pairs of electrodes and for all subjects.

From Table 3, we can see that some pairs of electrodes have high positive CS values, which means that they are correlated to the emotion, and they can be used to estimate the emotion.

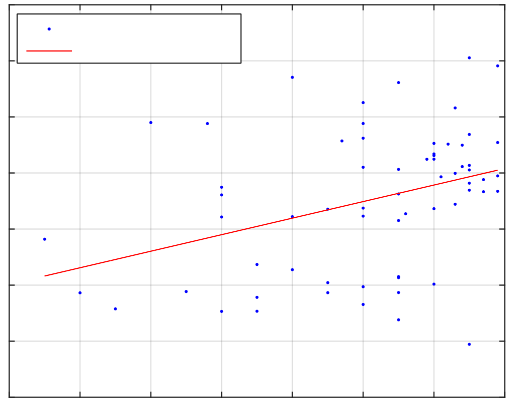

Figure 8: Average FA_{xy} versus emotion of the pair F7-FC5

Table 3: Coherence Slope (CS) of Selected Pairs

Pair Name	CS%	Pair Name	CS%
F7-FC5	2.288	F7-FC6	0.5304
AF3-F7	2.157	AF4-F3	0.4484
AF3-FC5	1.621	AF3-F8	0.3393
AF3-AF4	1.489	F3-F4	0.3139
F3-FC5	1.479	AF3-FC6	0.05809
AF4-FC5	1.42	F3-FC6	0.02811
F4-FC5	1.369	AF3-F3	0.01177
AF4-F7	1.363	F4-FC6	-0.02839
F3-F7	1.269	AF4-F4	-0.1085
F4-F7	1.23	F3-F8	-0.1662
F8-FC5	0.8892	AF4-F8	-0.1948
FC5-FC6	0.8515	AF4-FC6	-0.2343
F7-F8	0.6965	F4-F8	-0.4114
AF3-F4	0.5337	F8-FC6	-0.6889

4.0 CONCLUSION AND FUTURE WORK

In this work, a wavelet coherence analysis is performed on EEG recordings acquired from 14 healthy subjects while they are listening to verses from the Quran recited by different reciters. The results showed that some pairs of electrodes exhibit more correlation with the emotions reported by the subjects. More specificity, the results showed that the pair AF3-F7 possess the higher correlation value and it could be used to estimate the subject's emotion from its wavelet coherence value.

As a future work, the proposed emotional model will be evaluated in real time application. Moreover, other averaging and fitting methods could be considered.

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