Evidence Accumulation Approach applied to EEG Analysis

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Keywords: EEG, ICA, EMD, Phase-locking Factor, Clustering Ensembles.

Abstract: Human-machine interaction is a rapidly expanding field which benefits from automatic emotion recognition. Therefore, methods that can automatically detect the emotional state of a person are important for this field, as well as for fields such as psychology and psychiatry. This paper proposes the use of clustering ensembles (CEs) to achieve such detection. We use CEs on a dataset containing EEG signals from subjects who performed a stress-inducing task. From the raw EEG data we apply filtering and processing techniques leading to three dataset types: simple EEG, EEG with eye-movement artifacts removed through Independent Component Analysis, and data-driven modes extracted using Empirical Mode Decomposition. Then, for each of these three data types, we compute band power features and phase-locking factors, yielding a total of six different feature spaces. These spaces are then analyzed using the CE framework which combines results of multiple clustering algorithms in a voting scheme. This procedure yields interesting clusters, in particular a natural tendency for finding low numbers of clusters per subject and finding clusters which are composed of consecutive test lines. These two facts combined may indicate that a change in the emotional state of the subject was detected by the proposed framework.

1 INTRODUCTION

There are hundreds of clustering algorithms, handling differently issues such as cluster shape, density, noise, among others (Jain et al., 1999; Theodoridis and Koutroumbas, 2009). Examples of application include bioinformatics, market research, and medicine.

However, the simple use of a clustering algorithm like k-means can give a diversity of solutions over the same dataset depending of the initialization, or of the chosen k. Recently, an approach known as *Clustering Ensemble* (CE) has been proposed, taking advantage of that diversity of solutions (Fred, 2001; Strehl and Ghosh, 2002; Kuncheva and Hadjitodorov, 2004; Ayad and Kamel, 2005). CEs can be generated from different clustering algorithms or algorithmic parameters over data. CEs have been applied to various domains including image segmentation, bioinformatics, document clustering, among several others (Vega-Pons and Ruiz-Shulcloper, 2011).

In this paper, we analyze electroencephalogram (EEG) data using the CE framework. This EEG data was acquired from subjects performing a stressful task, which requires high concentration levels over a long time. This design mimics what may occur during interactive educational tasks, where detecting when a subject is growing tired would be useful.

Typical pre-processing of EEG signals usually involves the extraction of band power features (BPFs), since brain activity measured on the scalp exhibits oscillatory dynamics which are modulated by neurological tasks (Pfurtscheller and Lopes da Silva, 1999). As an example, a phenomenon called Event-Related Desynchronization, which involves a decrease of the EEG power in the motor cortex, usually occurs during movement preparation (Pfurtscheller and Lopes da Silva, 1999). A disadvantage of BPFs is that they require *a priori* selection of the frequency bands, which may not be constant between subjects. Alternatively, the Phase-Locking Factor (PLF) method has been proposed in the area of Brain-Computer Interfaces (Carreiras et al., 2012); we apply this method here in the context of emotion analysis.

This paper is organized as follows: Section 2 describes the acquisition of the EEG signals. Section 3 details the proposed methodology, which has three main stages: signal processing (3.1), feature extraction (3.2) and clustering ensembles (3.3). Section 4 presents the results of this methodology on the EEG data. Section 5 presents concluding remarks.

Aidos H., Carreiras C., Silva H. and Fred A. (2013).
Evidence Accumulation Approach applied to EEG Analysis.
In *Proceedings of the 2nd International Conference on Pattern Recognition Applications and Methods*, pages 479-484
DOI: 10.5220/0004267804790484

2 EMOTION ELICITATION AND DATA ACQUISITION

The EEG signals used throughout this work were acquired in the context of HiMotion (Gamboa et al., 2007), a project whose goal was to obtain information related to human-computer interaction and physiological signals on different cognitive activities. Signals were obtained at four scalp positions, according to the 10-20 system (F_{p1}, F_z, F_{p2}, and O_z – see Figure 1), at a sampling rate of 256 Hz. The data was acquired from 24 subjects (17 males and 7 females) with ages in the range of 23.3 ± 2.4 years.

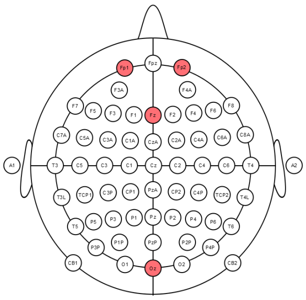

Figure 1: Electrodes placement used in our setup (red).

During data acquisition, subjects were instructed to perform several cognitive tasks. One of these tasks, a concentration task, was inspired by a test from the MENSA set (Fulton, 2000). The person is presented with a screen containing a matrix with 20 rows and 40 columns of integers. The goal is to identify pairs of consecutive numbers which sum to 10 (see Figure 2). This task is cognitively challenging, since the same number may be used to form two pairs; thus, the test assesses the ability of the person to maintain concentration over long periods of time, an activity which is expected to induce stress.

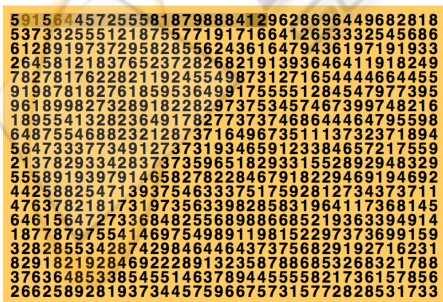

Figure 2: A matrix of the concentration test; the user selects, line by line, the pairs of consecutive numbers that add to 10.

3 THE PROPOSED METHODOLOGY

To analyze the EEG signals described in the previous section, we propose the methodology shown in Figure 3. We start with a filtering step, followed by a denoising process using independent component analysis (ICA) and empirical mode decomposition (EMD). Then, we perform feature extraction using two different measures: band-power features (BPF) and phase-locking factor (PLF). Finally, we use the CE framework on these features and analyze the results to detect changes in the emotional state. We explain each of these steps in detail in the following subsections.

3.1 Signal Processing

To eliminate noise from non-physiological sources, such as power-line noise and baseline wander, the raw EEG was processed with two Butterworth filters, each applied on a forward pass and then a backward pass (to avoid distortions in the phase of the signals). The first filter is a high-pass filter of order 8 with cutoff frequency at 4 Hz, while the second one is a low-pass filter of order 16, with cutoff at 40 Hz. Three distinct methods were used to create features: in the first, we apply no further processing and use the filtered EEG directly; we call this the EEG-only approach. In the second method, we apply Independent Component Analysis (ICA) to remove eye-movement artifacts; we call this method EEG-ICA. In the third method, we apply Empirical Mode Decomposition (EMD), a method which analyzes non-stationary and non-linear data; this approach is denoted as EEG-EMD.

3.1.1 Independent Component Analysis

We now introduce Independent Component Analysis (ICA), a method to solve blind source separation problems (BSS). Let $\mathbf{X} = [X_1, ..., X_M]^T$ (M being the number of signals) be the observed data produced by a linear mixture $\mathbf{X} = \mathbf{AS}$ of some source signals $\mathbf{S} = [S_1, ..., S_N]^T$ (N being the number of sources), where $\mathbf{A}$ is an $M \times N$ matrix.

The goal of the BSS problem is to find the sources $\mathbf{S}$ and the mixing matrix $\mathbf{A}$, using only the observed signals $\mathbf{X}$. One way to do so is ICA, which assumes that $S_1, S_2, \ldots, S_N$ are statistically independent. The ICA methods estimate the sources by optimizing a measure of their independence (which depends on the particular ICA algorithm), yielding sources that are maximally independent (Hyvärinen et al., 2001).

ICA has been used effectively to separate meaningful neural activity from artifacts due to muscle

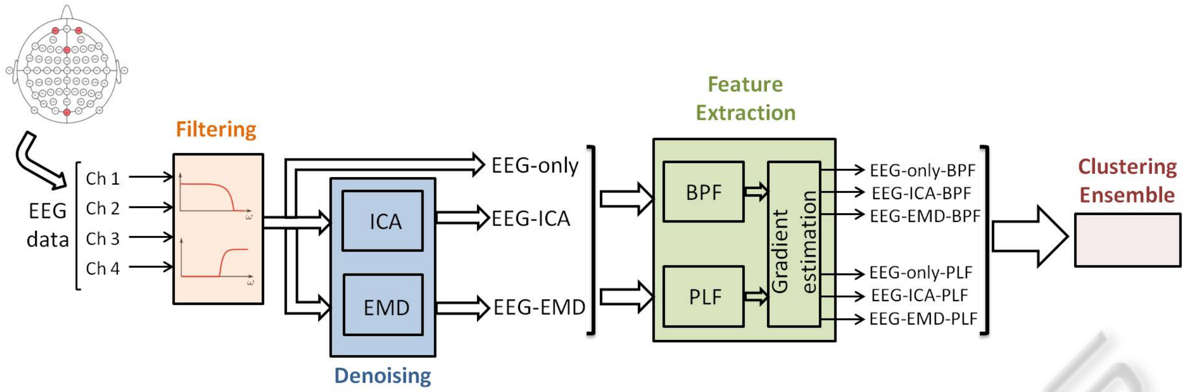

Figure 3: Outline of the proposed methodology.

contractions and eye blinks in EEG data (Jung et al., 2000). In this paper, we used *FastICA* (Hyvärinen et al., 2001) to decompose the EEG into independent components. Then, one of the four retrieved components was manually selected as the one which best isolated eye artifacts; this component was discarded and the EEG was reconstructed without that component. An example of the original EEG signal, its ICA decomposition and reconstruction without the noisy component can be seen in Figure 4.

3.1.2 Empirical Mode Decomposition

Empirical Mode Decomposition decomposes a signal into a sequence of oscillatory-like components called Intrinsic Mode Functions (IMFs), using a sifting process (Huang et al., 1998). It is a data-driven method: it estimates two envelopes, one bounding the signal from above and one from below, by interpolating the local maxima and minima of the signal; it then computes the mean of these two envelopes as a running average of the signal and subtracts it from the signal, thus leaving a deviation from this running average. This process is then restarted, using the deviation as a new input signal, and so on. In this way, one can extract a sequence of IMFs from the original signal.

In this paper, each EEG signal was decomposed with the EMD method, selecting the IMFs with mean energy above 5% of the maximum energy. The resulting components were treated as EEG-like signals for the subsequent processing steps.

3.2 Feature Extraction

The features used in this work come from two ways of evaluating brain activity. The first method uses band power features (BPF), where we compute the average power in multiple frequency bands (Section 3.2.1). The second approach uses the Phase-Locking Factor (PLF – Section 3.2.2), which is a measure of synchrony. One of the difficulties in the analysis of signals resulting from a continuously interactive experiment, such as the one being analyzed here, is the fact that different subjects will finish the task in different time intervals. In our case, there is variability in the time each subject takes to conclude each line of the concentration test, and thus, in the total length of the task. For this reason, we used a gradient estimation to evaluate the trend of each type of features (BPF and PLF) over time, obtaining a value for each line of the matrix in the concentration test (Section 3.2.3).

It is important to highlight that each of the preprocessing methods (EEG-only, EEG-ICA and EEG-EMD) was analyzed with both kinds of features (BPF and PLF), resulting in 6 different sets of features. For clarity, we denote each set by the combination of the two respective names. For instance, the feature set "EEG-ICA-PLF" was obtained by extracting the PLF features from the EEG preprocessed with ICA.

3.2.1 Band Power Features

We consider the following bands in the Band Power Features approach: Theta (4-8 Hz); Lower Alpha (8-10 Hz); Upper Alpha (10-13 Hz); Beta (13-25 Hz); Gamma (25-40 Hz). For each channel, we extracted the features by computing a short-time Fourier transform in windows of 500 ms, with 50% overlap. The windowed signal was completed with zeros up to 1024 samples. The power in each band was computed by averaging the spectrum in that band. An order 5 median filter was then applied to the resulting signals.

3.2.2 Phase-locking Factor

Given two oscillators i and k with time-dependent phases $\phi_i[n]$ and $\phi_k[n]$, $n = 1, ..., T$ (with T the number of discrete time samples), the PLF is defined as (Almeida et al., 2011):

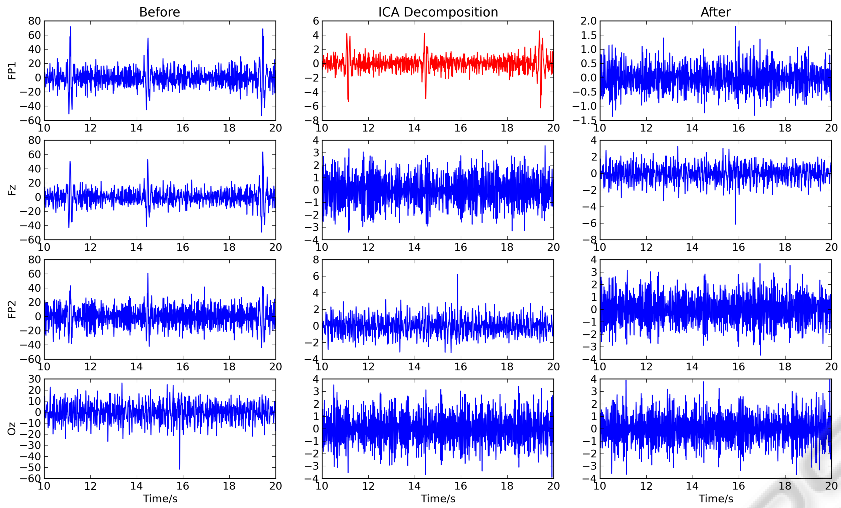

Figure 4: Example of applying the ICA method to remove eye-movement artifacts from the EEG; the left column shows the four original EEG channels, where the spikes are ocular artifacts; the middle column shows the ICA decomposition, with removed component in red; and the right column presents the reconstructed EEG.

$$\rho_{ik} = \left| \frac{1}{T} \sum_{n=1}^{T} e^{j(\phi_i[n]-\phi_k[n])} \right|, \tag{1}$$

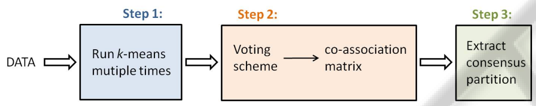

Figure 5: Outline of the evidence accumulation framework.

where $j = \sqrt{-1}$ is the imaginary unit. This measure ranges from 0 to 1. While the value $\rho_{ik} = 1$ corresponds to perfect synchronization between the two signals (constant phase lag), the value $\rho_{ik} = 0$ corresponds to no synchronization. Put simply, the PLF measures whether the phase lags of some pair of oscillators are strongly or weakly clustered around some angle in the complex unit circle. In this work, phase information is extracted from the EEG signals (which are real-valued) through the use of analytical signals, which are obtained by applying the Hilbert transform to the EEG signals. Given a real signal $x(t)$, its Hilbert transform is defined as $\mathcal{H}_t\{x\} = x(t) * \frac{1}{\pi t}$, where $*$ denotes the convolution operator; the corresponding analytical signal $z(t)$ is then obtained as:

$$z(t) = x(t) + j\mathcal{H}_t\{x\} = x(t) + j\left[x(t) * \frac{1}{\pi t}\right]. \tag{2}$$

The PLF was computed, for all possible electrode pairs, in windows of 250 ms, with 50% overlap. An order 5 median filter was then applied.

3.2.3 Gradient Estimation

In order to estimate the trend of the feature sets over time, a straight line was fitted to each line $k = 1, \ldots, 20$ of the concentration task (with $T(k)$ duration), estimating the gradient $G(k)$ of that line. The evolution of the features, from the initial state, over the lines is then given by $D(k) = D(k-1) + G(k) \times T(k)$, with $D(0) = 0$.

3.3 Evidence Accumulation Clustering

Consider $\mathcal{X} = \{x_1, x_2, \ldots, x_n\}$ a set of n objects. A *clustering ensemble*, $\mathbb{P}$, is a set of N different partitions of the data $\mathcal{X}$, where each partition is the output of a clustering algorithm:

$$\begin{aligned} \mathbb{P} &= \{P^1, P^2, \ldots, P^N\} \\ P^1 &= \{C_1^1, C_2^1, \ldots, C_{k_1}^1\} \\ &\vdots \\ P^N &= \{C_1^N, C_2^N, \ldots, C_{k_N}^N\}, \end{aligned} \tag{3}$$

where C_j^i is the jth cluster in data partition P^i, which has k_i clusters, and n_j^i is the cardinality of C_j^i, with $\sum_{j=1}^{k_i} n_j^i = n, i = 1, \ldots, N$.

(Fred and Jain, 2005) proposed a voting scheme to combine all the different partitions, under the *evidence accumulation* framework. This voting scheme leads to a pairwise relationships matrix, called "co-association matrix":

$$C(i,j) = \frac{n_{ij}}{N}, \tag{4}$$

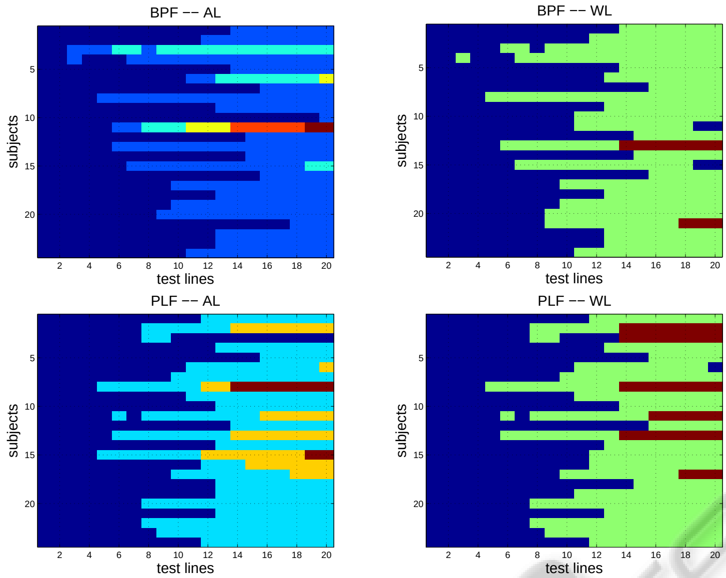

Figure 6: Each of the four subfigures represents one of the combinations of feature type (BPF or PLF) and clustering algorithm (AL or WL). Within each subfigure, each row represents one subject, and each column one of the test lines of the matrix in the concentration test. Each different color corresponds to a distinct cluster.

where n_{ij} is the number of times the pattern pair (i, j) is assigned to the same cluster among the N partitions.

According to (Fred and Jain, 2005), the evidence accumulation approach is a three-step cluster ensemble method (illustrated in figure 5):

Step 1: build the clustering ensemble (CE);

Step 2: combine evidence in the CE, mapping it into a co-association matrix;

Step 3: extract the consensus partition by applying a clustering method over the co-association matrix.

In order to produce the clustering ensembles, we perform 100 runs of k-means with k randomly chosen from the set $\{2,3,4\}$ for each feature space mentioned previously. We combined in a co-association matrix the 300 partitions using BPF and in a different co-association matrix the 300 partitions using PLF. After that we extract the consensus partition over each co-association matrix by applying two hierarchical clustering algorithms: average-link (AL) and Ward's linkage (WL). The final number of clusters is found using the largest lifetime criterion (Fred and Jain, 2002).

4 EXPERIMENTAL RESULTS AND DISCUSSION

The results of the previously described methodology are presented in Figure 6, from which one can draw some interesting conclusions. For example, the results of the two clustering algorithms are usually very close: in one of the cases, subjects 1, 2, 7, 8 and many others get exactly the same clustering from the BPF features, regardless of the choice of clustering algorithm. This confers some strength in the clusters which are found, since they are detected by two different algorithms. However, WL always finds 2 or 3 clusters, whereas AL occasionally finds 4 or more; this may suggest that WL is a better algorithm to use for emotion state change, as discussed below.

Going into the finer details, subject 11 was found to have 6 clusters by AL on the BPF features, but only 2 or 3 on the remaining three configurations. This suggests that subject 11 could be an outlier for some reason, such as improper experimental setup or inability to understand the instructions or to fulfill the task.

However, the most striking conclusion is that, in general, two clusters are found for each subject, and each cluster is usually composed of consecutive test lines. In other words, each cluster represents a single time interval. This can be interpreted as a detection of a change in the emotional state of the subject during the task, for example due to difficulty in maintaining appropriate concentration levels which could lead to feelings of tiredness, frustration, or stress.

To assess whether this detection of emotional state change is correct or not, one would need data which contains ground truth information about the emotional state of each subject. One possibility is to ask subjects directly to indicate their self-assessed concentration level, for example at the end of each line. Another possibility is to use the time it took the subject to complete the task as a proxy for his/her concentration level: it is intuitive that lines which took longer to finish did so because the subject was maintaining a lower concentration level. A third possibility is to use lines of different difficulty (with harder lines having more pairs of numbers to be indicated), and assume that harder lines will induce more stress. Acquisition of data with this type of external information, and its subsequent analysis using the methodology proposed here, will be the subject of future work.

5 CONCLUSIONS

We presented a methodology for exploratory data analysis of EEG data acquired while subjects performed a task which demands high concentration levels. We preprocessed the data using bandpass filtering, independent component analysis (ICA) and empirical mode decomposition (EMD); we then used two different measures: band power features (BPF) and phase-locking factor (PLF), which measure energy in typical EEG bands and phase synchrony across pairs of channels, respectively. Finally, we used the clustering ensembles framework to extract relevant information from those features.

The main conclusion is the finding of few clusters per subject and per test line (usually 2 or 3; 4 or more clusters are rare), and the fact that these clusters are almost always composed of a single time interval. These findings suggest that this methodology may be detecting a transition in the brain activity of the subject, which could be caused by a change in the emotional state due to tiredness or stress.

ACKNOWLEDGEMENTS

This work was supported by the Portuguese Foundation for Science and Technology grants PTDC/EIA-CCO/103230/2008 and SFRH/BD/65248/2009.

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