

Morphological ECG Analysis for Attention Detection

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Abstract: The electroencephalogram (EEG) signal, acquired on the scalp, has been extensively used to understand cognitive function, and in particular attention. However, this type of signal has several drawbacks in a context of Physiological Computing, being susceptible to noise and requiring the use of impractical head-mounted apparatuses, which impacts normal human-computer interaction. For these reasons, the electrocardiogram (ECG) has been proposed as an alternative source to assess emotion, which is also continuously available, and related with the psychophysiological state of the subject. In this paper we present a study focused on the morphological analysis of the ECG signal acquired from subjects performing a task demanding high levels of attention. The analysis is made using various unsupervised learning techniques, which are validated against evidence found in a previous study by our team, where EEG signals collected for the same task exhibit distinct patterns as the subjects progress in the task.

1 INTRODUCTION

Standard methods for communication between humans and computing systems, using a keyboard and mouse, or a touch screen, provide a very limited information bandwidth when compared to the richness of the user's psychophysiological state (Fairclough, 2009). Indeed, in natural human communication, the speaker's attitude, posture, tone, and facial expressions, among others, strongly influence the semantic interpretation done by the receiver (Pell et al., 2011). These characteristics are often related with the emotional state of the speaker, adding an extra layer of information that a computer cannot yet easily understand. The integration of this psychophysiological information into computer systems, by continuous, real-time monitoring of the user, is known as Physiological Computing (Fairclough, 2009).

Straightforward approaches to physiological computing, requiring no extra hardware, are, for example, keystroke dynamics (Epp et al., 2011), speech analysis (Murray and Arnott, 1993), and automatic facial expression recognition (Zheng et al., 2006). However, all these examples exhibit serious problems to their usefulness. Keystroke dynamics requires continuous typing, speech analysis requires continuous speech, in addition to disclosing sensitive and/or private information to possible eavesdroppers, and a facial expres-

sion is a vague concept to be described objectively, with its usefulness for behavioral science being questioned in (Aviezer et al., 2012). One possible alternative to these modalities, although requiring extra hardware, is the use of the subject's biosignals (e.g. electrodermal activity, peripheral temperature, blood volume pulse, electrocardiogram, electroencephalogram signals), acquiring them during normal human-computer interaction tasks (Canento et al., 2011; Silva et al., 2012). These signals have the twofold advantage of being always available, and measuring the natural physiological responses of the body to a given affective state, which cannot be voluntarily masked.

The electroencephalogram (EEG) signal, acquired on the scalp, has been extensively used to understand cognitive function, and in particular emotion (Ahern and Schwartz, 1985; Coan and Allen, 2007), being a noninvasive, cost-effective technique, with good temporal resolution (Mak and Wolpaw, 2009). However, it has various drawbacks, such as susceptibility to noise (in particular motion artifacts and eye blinks) and, most importantly, requires the use of some kind of head-mounted equipment to support the (typically wet) electrodes, which becomes impractical for continued use. In this context, the electrocardiogram (ECG) signal has been suggested as a possible option (Medina, 2009; Belle et al., 2010). Nevertheless, the usefulness of the EEG as source of ground-truth in-

formation has not been discarded (Belle et al., 2012).

In this paper, we make a morphological analysis, using unsupervised learning techniques, of the ECG acquired from subjects performing a task that demands high levels of attention over a long period of time. This experiment simulates what may happen, for instance, during an interactive educational game, extended work hours, repetitive daily tasks, or sleep deprivation, where attention levels fluctuate throughout the execution of the task. This is particularly important in various professions, such as doctors, pilots, drivers or industrial equipment operators, for which momentary or prolonged lapses of attention may be catastrophic (Belle et al., 2012). In addition, we compare the results obtained with the ECG signal to our previous work using the EEG, which provided evidence that the subjects indeed exhibit distinct affective states throughout the completion of the task (Carreiras et al., 2013).

The remainder of the paper is organized as follows: Section 2 describes the experimental setup. Section 3 details the proposed methodology, including the description of the clustering methods used, as well as several clustering validation metrics. Section 4 presents the obtained results, which are discussed in Section 5. Finally, Section 6 concludes the paper.

2 AFFECTIVE ELICITATION AND DATA ACQUISITION

The ECG signal presents several attributes that make it especially interesting in a physiological computing framework. Specifically, it is continuously available, providing a rich wellbeing indicator, is related with the psychophysiological state of the subject, and is easy to acquire unobtrusively with wearable devices. This is further enhanced by following an *off-the-person* approach, where the sensors are seamlessly integrated into objects with which subjects regularly interact, such as a keyboard, a video game controller, or a mobile device, without the need to change normal interaction patterns (Silva et al., 2011).

It is widely known that the basic function of the heart is to pump blood throughout the body, demanding a highly synchronized sequence of muscular contractions. These contractions are initiated by small electrical currents that propagate through the heart's muscle cells, generating an electrical signal that can be recorded at the body surface (the ECG). In healthy individuals, the electrical activity of the heart is guided by the self-excitatory nature of the sinus node on the left atrium (see Figure 1), which

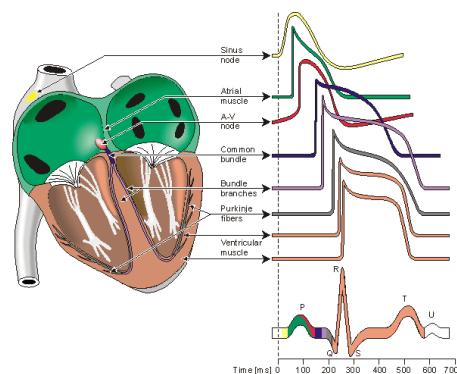


Figure 1: Schematic representation of the heart compartments and its electric system, showing the contribution of each component to the prototypical heartbeat signal recorded at the body surface (used with permission from (Malmivuo and Plonsey, 1995)).

naturally produces electrical depolarizations at a rate of about 100 beats per minute. However, the sinus node is under systemic control by the endocrine system and the Autonomic Nervous System (ANS). The ANS is composed by two complementing, self-balancing subsystems, the Sympathetic and Parasympathetic Nervous Systems (SNS and PSNS, respectively). While the SNS is typically responsible for the promotion of *fight-or-flight* responses in the organism (e.g. by increasing the heart rate), the PSNS is responsible for the promotion of *rest-and-digest* responses, which induce relaxation and a return to normal function. As a whole, the ANS provides an access route to the affective state of a person (Levenson, 1992), by analyzing the patterns of physiological activity initiated by both the SNS and PSNS. In particular for the ECG, the amplitude and latency of the P-QRS-T complexes is influenced by multiple psychophysiological factors, and some changes in the user's behavior result in slight variations in the heart rate and waveform morphology.

The ECG and EEG signals analyzed here were acquired in the context of the HiMotion project (Gamba et al., 2007), an experiment to acquire information related to human-computer interaction and physiological signals on different cognitive activities. During the experimental session, the subjects were asked to execute various interactive cognitive tasks. Particularly, a concentration task was performed, adapted from a similar test from the MENSA set (Fulton, 1999). In this test, the subject is presented with a matrix of 800 integers (20 lines by 40 columns), as shown in Figure 2. The goal of the game is to identify, line by line, all the pairs of consecutive numbers that add to 10. This task requires high levels of attention, as the pairs may overlap (i.e. the same number

may belong to two pairs), measuring the capacity of the subject to maintain an attentive state over a long period of time.

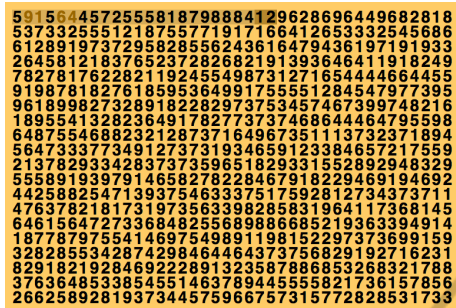


Figure 2: Example matrix of the concentration test; the user selects, line by line, the pairs of consecutive numbers that add to 10.

Biosignal data was obtained from 24 subjects (17 males and 7 females) with ages in the range 23.3 ± 2.4 years, using a *Thought Technology ProComp2* acquisition system, with a sampling rate of 256Hz . The ECG was acquired with Ag/AgCl electrodes placed on the chest (4th intercostal space in the mid clavicular line), while the EEG was acquired at four scalp locations according to the 10-20 system (F_{p1} , F_z , F_{p2} , and O_z), as shown in Figure 3.

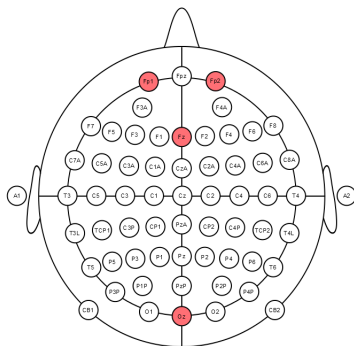


Figure 3: Locations of the acquired EEG electrodes on the scalp (red).

3 PROPOSED METHODOLOGY

It should be noted that each person has different characteristics in terms of attention span and, as such, aside from the temporal information regarding the start and the end of each line of the attention game, no more information is available for this data set. Particularly, there is no ground-truth information regarding the time instants in which the affective state of each

test subject has really changed. For this reason, we propose the use of unsupervised learning techniques to analyze the ECG data.

The proposed methodology is presented in Figure 4 and it is divided in three main stages: feature extraction, clustering, and validation of the clustering results. We start by filtering and segmenting the raw ECG, and then we apply clustering techniques to analyze the data. Subsequently, the results of those clustering algorithms are validated using several metrics, exploiting our previous analysis of the same data set with the EEG signal (Carreiras et al., 2013). This somewhat follows the methodology proposed in (Belle et al., 2012), where the EEG signal is used as a benchmark against which the performance of attention recognition via the ECG is compared. All these stages are explained in the following subsections.

3.1 ECG Feature Extraction

Raw ECG signals are typically affected by various noise sources such as motion artifacts, power line interference, and electromyographic noise. To enhance the signal-to-noise ratio (SNR), and to reduce the influence of the cited noise sources, we used a band-pass Finite Impulse Response (FIR) filter with a Hamming window of 300ms , and cutoff frequencies of $5 - 20\text{Hz}$. The filtered signal was then fed to a segmentation algorithm, with the purpose of identifying the locations of the R peaks. For that we used the algorithm by Engelse and Zeelenberg (Engelse and Zeelenberg, 1979), with the modifications proposed in (Canento et al., 2013). Individual heartbeat segments of 600ms were extracted from the filtered signal, between 200ms before and 400ms after the R peak. Finally, in order to further improve the SNR, heartbeat templates were formed using sequences of 5 consecutive heartbeats, computing their element-wise mean (an example of these templates can be seen in Figure 5). These templates form the feature space used by the clustering algorithms, described in Section 3.3.

3.2 EEG Feature Extraction

Our previous work, focusing on the EEG signal, is based on two distinct feature extraction techniques. The first follows the traditional approach of analyzing the various EEG frequency bands, the Band Power Features (BPF). Specifically, we used the theta (from 4 to 8 Hz), lower alpha (from 8 to 10 Hz), upper alpha (from 10 to 13 Hz), beta (from 13 to 25 Hz), and gamma (from 25 to 40 Hz) bands. The second approach uses a method of synchronization quantifica-

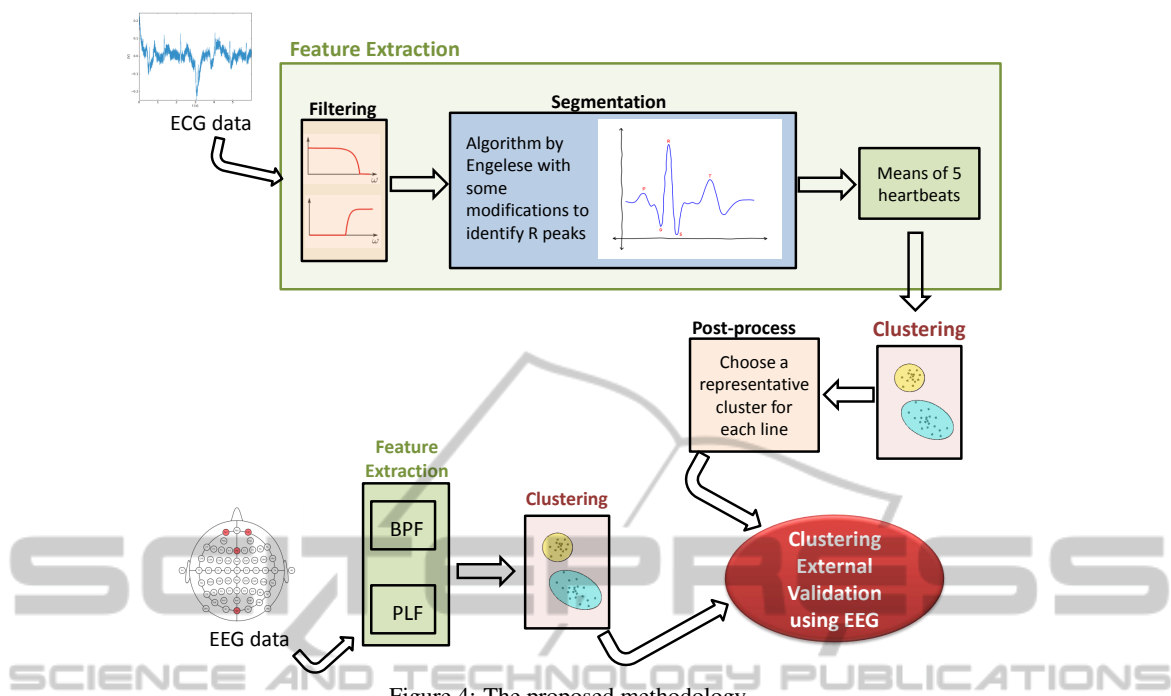


Figure 4: The proposed methodology.

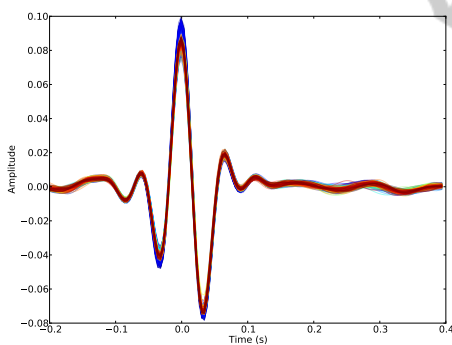


Figure 5: ECG templates obtained for subject 11.

tion, the Phase-Locking Factor (PLF), which leverages the fact that EEG signals exhibit an oscillatory behavior whose phase dynamics are modulated by the neurological tasks (Pfurtscheller and Lopes da Silva, 1999). The PLF between two signals is defined as (Almeida et al., 2009):

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

where $\phi_i[n]$ and $\phi_k[n]$, $n = 1, \dots, T$ are the phases of the signals, T is the number of discrete time samples, and $j = \sqrt{-1}$ is the imaginary unit. This measure ranges from 0 to 1, with a value of $\rho_{ik} = 1$ corresponding to perfect synchronization between the two signals (constant phase lag), while the value $\rho_{ik} = 0$ corresponds to no synchronization. These two feature

extraction methods form distinct feature spaces, upon which clustering methods were applied.

3.3 Unsupervised Learning

3.3.1 Clustering

Clustering is one of the central problems in Pattern Recognition and Machine Learning. Hundreds of clustering algorithms exist, differently handling issues such as cluster shape, density, and noise, among other aspects. These techniques require the definition of a similarity measure between patterns, be it geometrical or probabilistic, which is not easy to specify in the absence of any prior knowledge about cluster shapes and structure.

One of the classical approaches for clustering is the use of hierarchical agglomerative algorithms (Jain and Dubes, 1988), which produce a tree of nested objects (the dendrogram) that establishes the hierarchy between the clusters. These methods only require a measure of (dis)similarity and a linkage criterion between instances, while partitional methods (e.g. k -means or k -medoids) also require *a priori* the number of clusters, and an initial assignment of data to clusters. The linkage criterion allows to choose how to define intergroup similarity. In particular, we apply the Average Link (AL) and Ward's Linkage (WL) criteria (Theodoridis and Koutroumbas, 1999). Furthermore, to obtain a partition of the

data from a dendrogram, we use the largest lifetime criterion (Fred and Jain, 2002).

Moreover, we use a new high order dissimilarity measure, called *dissimilarity increments*, proposed by (Fred and Leitão, 2003). This measure is computed over triplets of nearest neighbor patterns and is defined as:

$$d_{inc}(x_i, x_j, x_k) = |D_*(x_i, x_j) - D_*(x_j, x_k)|, \quad (2)$$

where x_j is the nearest neighbor of x_i , and x_k is the nearest neighbor of x_j , different from x_i . In equation (2), $D_*(\cdot, \cdot)$ can be any dissimilarity measure, such as the Euclidean distance. The dissimilarity increments measure can give more information about patterns belonging to the same cluster, since it changes smoothly if the patterns are in the same cluster. In (Aidos and Fred, 2011), an agglomerative hierarchical algorithm, called SLDID, was proposed. This algorithm is a variant of the Single Link (SL) criterion using the dissimilarity increments distribution (DID), which was derived under mild approximations in (Aidos and Fred, 2012), to modify the way that clusters are merged. In this paper we used a family of DID algorithms: ALDID and WLDID. They are variants of the traditional hierarchical clustering algorithms AL and WL, respectively. The main difference between AL and ALDID is that in AL, in each iteration the pair of clusters with the highest cohesion is always merged; in ALDID some tests are made using the minimum description length (MDL) criterion between two possibilities. These two possibilities consist in the DID of the two clusters combined, and the DID of the two clusters separated. One advantage in using an algorithm from this family is that it stops merging clusters before all the data is merged into one cluster, revealing intrinsic cluster structure in the data when the true number of clusters is unknown.

3.3.2 Consensus Clustering

Consensus clustering, also known as Clustering combination, is a powerful technique that combines the information of multiple clustering partitions, forming a *clustering ensemble* (\mathbb{P}), and creating a consensus partition that leverages the results of individual clustering algorithms. Recent surveys present an overview on this research topic (Ghosh and Acharya, 2011; Vega-Pons and Ruiz-Shulcloper, 2011). One of the significant approaches is the Evidence Accumulation Clustering (EAC) (Fred and Jain, 2005). This framework is based on the aggregation of object *co-occurrences*, and the consensus partition is obtained through a voting process among the objects. Specifically, the consensus clustering problem is addressed by summarizing the information of the ensemble into

a pairwise *co-association matrix*, where each entry holds the fraction of clusterings in the ensemble in which a given pair of objects is placed in the same cluster:

$$C(i, j) = \frac{n_{ij}}{N}, i, j \in 1, \dots, N. \quad (3)$$

For the construction of the ensemble, we use the k -means algorithm (Jain and Dubes, 1988) with different parameters and initializations. We created a set of $N = 100$ partitions¹ by randomly choosing the number of clusters, following the work by (Lourenço et al., 2010) where the minimum and maximum number of clusters per partition depends on the number of objects n , and is bound to the interval $[\frac{\sqrt{n}}{2}, \sqrt{n}]$.

The extraction of the consensus partition can be performed using several approaches based on the induced co-association matrix: i) as a new (dis)similarity-based representation of objects, where the intrinsic structure of the data is enhanced through the evidence accumulation process, enabling the determination of the consensus partition using algorithms that explicitly use similarities as input, such as hierarchical linkage methods (as classically performed in (Fred and Jain, 2005)); ii) as a new vector-based object description, considering each line of the matrix a new feature vector representation, and using it as input to a clustering algorithm such as the k -means (Kuncheva and Vetrov, 2006); iii) as a new probabilistic distribution characterized by the probability of pairs of objects being in the same cluster (Lourenço et al., 2013).

3.3.3 Application to EEG and ECG

The focus of this work was the unsupervised analysis of the ECG signals, and for that we applied all the described techniques: i) hierarchical agglomerative algorithms; ii) hierarchical agglomerative algorithms with dissimilarity increments; iii) consensus clustering based on evidence accumulation clustering, using as extraction criterion the average linkage method with the number of clusters automatically determined by the life-time criterion.

The clustering of the ECG heartbeats was performed over the means of 5 consecutive heartbeats. Since we are willing to compare these partitions with the ones obtained on the context of EEG, where for each line of the test there is only one cluster, it was necessary to post-process the obtained partitions, choosing as representative cluster for each line the one with highest cardinality (largest time span).

¹This is the number typically proposed in the reference literature.

In the context of EEG clustering, we applied the hierarchical agglomerative methods with and without dissimilarity increments.

3.4 Cluster Validation

Cluster validation techniques have been developed to guide the design of clustering experiments and to assess the quality of the outcome. There are three types of cluster validity measures (Dubes and Jain, 1979; Halkidi et al., 2001; Meilă, 2007; Ben-Hur et al., 2002; Luo et al., 2009): i) *External*: used to measure the goodness of a clustering structure with respect to external information; ii) *Internal*: used to measure the goodness of a clustering structure without supplying any class labels; and iii) *Relative*: used to compare different clusterings.

We adopt an external clustering validation perspective, using as external source of information the clusterings obtained with the EEG. There is a long list of external validation indices proposed in the literature (Meilă, 2007; Fowlkes and Mallows, 1983; Ben-Hur et al., 2002; Dom, 2001), which can be categorized as follows: i) *Counting Pairs Methods*: a class of criteria based on counting the pairs of points on which two clusterings agree/disagree, Wallace (Wallace, 1983), Fowlkes and Mallows (Fowlkes and Mallows, 1983), and Rand's (Rand, 1971) are the most representatives of this class; ii) *Set Matching*: based on set matching cardinality, \mathcal{H} criterion (Meilă, 2007), and consistency index (Ci) (Fred, 2001; Duarte et al., 2011) are representative of this class; iii) *Information Theoretic*: based on information theoretic concepts (entropy and mutual information); representatives of this class of criteria are the Variation of Information (VI) index (Meilă, 2007) and Dom's index (Dom, 2001)

In this work, we compare the partitions obtained with the ECG with the ones obtained with the EEG (taken as ground-truth), and following the idea proposed in (Belle et al., 2012). We use indices of the three categories, to verify the consistency of the results in several perspectives, namely: Rand (Rand, 1971), a modified version of the Consistency Index entitled Average Cluster Consistency (ACC) (Duarte et al., 2011), and VI (Meilă, 2007). All the three indices take values between 0 and 1. Rand's index and the ACC take the value 1 for a perfect match between partitions, and for the VI index, 0 corresponds to a perfect match.

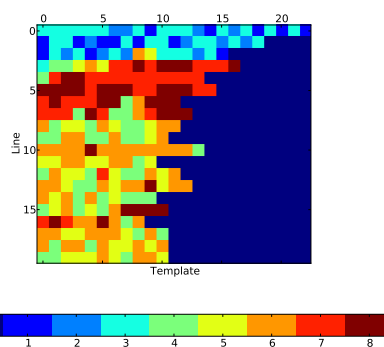


Figure 6: Clustering obtained for subject 11, using the clustering combination method, where each color represents a cluster, with a total of 8 clusters; *Bck* denotes the background color of the matrix.

4 EXPERIMENTAL RESULTS

Figure 6 exemplifies the clustering of the ECG templates obtained for one of the subjects, using the clustering combination (CC) method. It shows, for each line of the concentration task, the clusters to which the templates in that line belong to. The first observation to note is that the lines are not characterized by a single cluster, but rather by two or three clusters that alternate between them. However, it is possible to perceive the existence of different groups of lines. In this particular case, lines 0 to 2 are mainly composed by clusters 1, 2, and 3, lines 4 to 7 are composed by clusters 7 and 8, and the remaining lines are composed by clusters 4, 5, and 6. Another interesting note is the fact that the number of templates per line decreases throughout the completion of the task, implying that the first few lines of the task take longer to complete than the last lines. These observations are valid for the majority of the subjects, although the number of clusters and their distribution differs from subject to subject, forming different groups of lines.

Inter-subject variability is evidenced in Figure 7, where the clustering obtained, across all subjects, with the EEG (using PLF features and ALDID clustering – Figure 7(a)) is compared to the clustering obtained with the ECG (using CC clustering – Figure 7(b)). Remember that, in the case of the ECG, each line is represented by the most frequent cluster in that line. It is possible to observe that the ECG produces a higher number of clusters than the EEG, where each cluster tends to form groups of contiguous lines. Contrastingly, in the ECG it is frequent to have transitions to clusters seen in previous lines.

The results of the cluster validation are shown in Tables 1, 2, and 3 for the Average Cluster Consistency

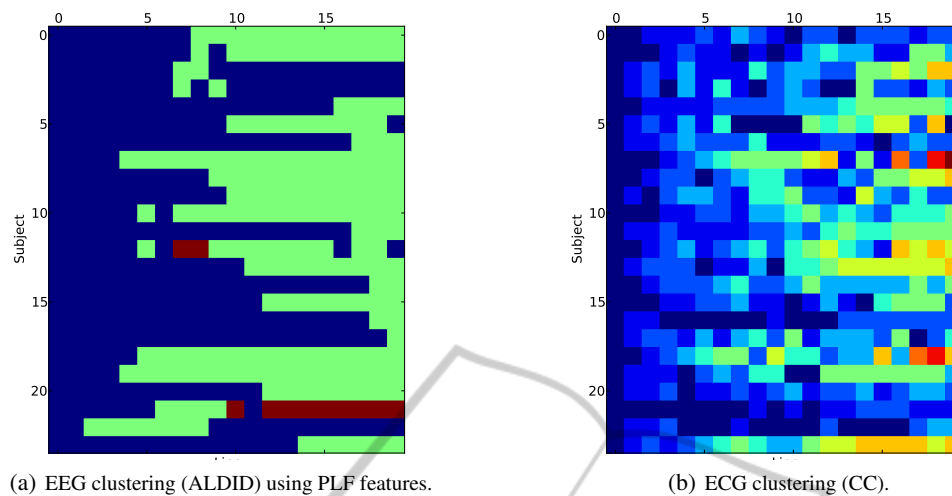


Figure 7: Comparison of the clustering obtained with the EEG to the one obtained with the ECG, across all subjects; each color represents one cluster.

(ACC), Variation of Information (VI), and Rand's index, respectively. For the ACC criterion, the highest agreement is obtained between the ECG clustering with CC and both the EEG clustering using AL (BPF) and ALDID (PLF), with a value of 0.79. Regarding the VI measure, the strongest agreements are seen for the ECG clustering using the AL algorithm, in particular with the ALDID method applied to the PLF features from the EEG, with a value of 0.20. Concerning Rand's index, the highest value, 0.63, is obtained between the ECG clustering through CC with the EEG clustering using WLDID (BPF).

5 DISCUSSION

Our work addresses the following questions: i) "Is ECG morphological analysis capable of identifying affective states throughout the realization of a task that demands a high attention span?"; ii) "Are the obtained states related to the ones found while analyzing EEG data?"; and iii) "What techniques can be considered to be more suitable for the analysis of the ECG?"

The validation of the partitions found using ECG, when considering the EEG partitions as ground-truth, shows that there is evidence of correlation between them, revealing that ECG can be used to infer affective states. The ECG partitions have a much higher number of partitions than the EEG ones, leading to distinct results over the various validation criteria (considering the different perspectives), associated with moderate to high matching. This was mainly due to small variations over time of the ECG heartbeats,

that lead to slow time transitions between the different clusters.

The clustering technique that presents the best results varies depending on the validation index. When considering the average cluster consistency (ACC), the consensus clustering (CC) obtains partitions that lead to a best match; when using variation of information (VI) criterion, the Average Link (AL) method is the one that leads to best match; and when using the Rand's index there is not a method which can be considered a clear winner. The situations with best results are partitions with high number of clusters, which correspond to Average linkage and Consensus Clustering.

6 CONCLUSIONS

In this work we present a methodology for attention detection based on the morphological analysis of ECG signals, using data collected during the course of a task requiring a high level of attention span. We compare the ECG morphology results with the analysis performed using the EEG. This comparison was accomplished using clustering validation indices.

The ECG analysis was divided into several steps. For the feature extraction step, the signal was first digitally filtered, segmented based on the peaks found by a modification of the Engelse and Zeelenberg algorithm, and templates were formed using means of 5 consecutive heart beats. For the clustering step, several state of the art techniques were used, since the ECG heartbeats have very small variations over time, leading to touching clusters.

Table 1: Cluster validation results ($\mu \pm \sigma$) using the Average Cluster Consistency (ACC) metric; higher values suggest a stronger agreement.

		ECG Clustering					
		AL	WL	ALDID	WLDID	CC	
EEG Clustering	AL	PLF	0.70 \pm 0.16	0.72 \pm 0.17	0.71 \pm 0.14	0.73 \pm 0.15	0.78 \pm 0.16
		BPF	0.70 \pm 0.15	0.74 \pm 0.15	0.70 \pm 0.18	0.72 \pm 0.17	0.79 \pm 0.15
	WL	PLF	0.61 \pm 0.12	0.65 \pm 0.16	0.62 \pm 0.11	0.67 \pm 0.13	0.76 \pm 0.17
		BPF	0.68 \pm 0.11	0.72 \pm 0.14	0.68 \pm 0.13	0.70 \pm 0.15	0.78 \pm 0.15
	ALDID	PLF	0.71 \pm 0.16	0.73 \pm 0.15	0.73 \pm 0.14	0.74 \pm 0.15	0.79 \pm 0.16
		BPF	0.55 \pm 0.13	0.60 \pm 0.16	0.55 \pm 0.14	0.60 \pm 0.14	0.69 \pm 0.14
	WLDID	PLF	0.62 \pm 0.16	0.66 \pm 0.16	0.64 \pm 0.14	0.69 \pm 0.16	0.77 \pm 0.18
		BPF	0.51 \pm 0.14	0.56 \pm 0.14	0.52 \pm 0.14	0.57 \pm 0.16	0.65 \pm 0.15

Table 2: Cluster validation results ($\mu \pm \sigma$) using the Variation of Information (VI) metric; lower values suggest a stronger agreement.

		ECG Clustering					
		AL	WL	ALDID	WLDID	CC	
EEG Clustering	AL	PLF	0.21 \pm 0.07	0.33 \pm 0.13	0.27 \pm 0.11	0.34 \pm 0.12	0.55 \pm 0.11
		BPF	0.22 \pm 0.09	0.32 \pm 0.11	0.28 \pm 0.09	0.35 \pm 0.14	0.55 \pm 0.11
	WL	PLF	0.26 \pm 0.06	0.36 \pm 0.11	0.32 \pm 0.08	0.37 \pm 0.11	0.54 \pm 0.13
		BPF	0.21 \pm 0.06	0.32 \pm 0.11	0.27 \pm 0.06	0.35 \pm 0.12	0.55 \pm 0.11
	ALDID	PLF	0.20 \pm 0.07	0.32 \pm 0.13	0.26 \pm 0.11	0.34 \pm 0.11	0.55 \pm 0.11
		BPF	0.34 \pm 0.10	0.40 \pm 0.13	0.38 \pm 0.09	0.43 \pm 0.12	0.55 \pm 0.10
	WLDID	PLF	0.25 \pm 0.08	0.36 \pm 0.12	0.31 \pm 0.10	0.36 \pm 0.12	0.55 \pm 0.11
		BPF	0.35 \pm 0.10	0.42 \pm 0.12	0.40 \pm 0.09	0.45 \pm 0.11	0.56 \pm 0.09

Table 3: Cluster validation results ($\mu \pm \sigma$) using Rand's metric; higher values suggest a stronger agreement.

		ECG Clustering					
		AL	WL	ALDID	WLDID	CC	
EEG Clustering	AL	PLF	0.59 \pm 0.15	0.59 \pm 0.14	0.59 \pm 0.12	0.54 \pm 0.10	0.49 \pm 0.11
		BPF	0.58 \pm 0.16	0.56 \pm 0.12	0.54 \pm 0.13	0.57 \pm 0.11	0.50 \pm 0.14
	WL	PLF	0.49 \pm 0.10	0.54 \pm 0.11	0.50 \pm 0.08	0.54 \pm 0.09	0.57 \pm 0.08
		BPF	0.56 \pm 0.11	0.57 \pm 0.13	0.52 \pm 0.06	0.55 \pm 0.08	0.51 \pm 0.11
	ALDID	PLF	0.61 \pm 0.16	0.59 \pm 0.14	0.60 \pm 0.13	0.53 \pm 0.11	0.48 \pm 0.12
		BPF	0.42 \pm 0.13	0.55 \pm 0.13	0.44 \pm 0.10	0.53 \pm 0.11	0.61 \pm 0.10
	WLDID	PLF	0.51 \pm 0.14	0.55 \pm 0.11	0.52 \pm 0.12	0.54 \pm 0.13	0.54 \pm 0.12
		BPF	0.39 \pm 0.13	0.53 \pm 0.13	0.42 \pm 0.11	0.51 \pm 0.12	0.63 \pm 0.10

Several clustering validation indices were used, trying to compare the partitions using different perspectives. Each of the validation indices showed that there is a high evidence of correlation between the partitions obtained by the ECG and the EEG. There is not a clear winner method, but Average Linkage and Consensus Clustering can be considered suitable methods for this kind of analysis.

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REFERENCES

- Ahern, G. L. and Schwartz, G. E. (1985). Differential lateralization for positive and negative emotion in the human brain: Eeg spectral analysis. *Neuropsychologia*, 23(6):745–755.
- Aidos, H. and Fred, A. (2011). Hierarchical clustering with high order dissimilarities. In *Proceedings of the 7th International Conference on Machine Learning and Data Mining (MLDM 2011)*, volume 6871 of *Lecture Notes in Computer Science*, pages 280–293, New York, USA.
- Aidos, H. and Fred, A. (2012). Statistical modeling of dissimilarity increments for d-dimensional data: Application in partitioning clustering. *Pattern Recognition*, 45(9):3061–3071.
- Almeida, M., Bioucas-Dias, J., and Vigário, R. (2009). Source separation of phase-locked subspaces. In *Proceedings of the International Conference on Independent Component Analysis and Signal Separation*, volume 5441, pages 203–210.
- Aviezer, H., Trope, Y., and Todorov, A. (2012). Body cues, not facial expressions, discriminate between intense positive and negative emotions. *Science*, 338(6111):1225–1229.
- Belle, A., Hargraves, R. H., and Najarian, K. (2012). An automated optimal engagement and attention detection system using electrocardiogram. *Computational and Mathematical Methods in Medicine*, 2012.
- Belle, A., Ji, S.-Y., Ansari, S., Hakimzadeh, R., Ward, K., and Najarian, K. (2010). Frustration detection with electrocardiograph signal using wavelet transform. In *IEEE International Conference on Biosciences (BIOSCIENCESWORLD)*, pages 91–94. IEEE.
- Ben-Hur, A., Elisseeff, A., and Guyon, I. (2002). A stability based method for discovering structure in clustered data. In *Pacific Symposium on Biocomputing*.
- Canento, F., Fred, A., Silva, H., Gamboa, H., and Lourenço, A. (2011). Multimodal biosignal sensor data handling for emotion recognition. In *Proceedings of the IEEE Sensors Conference*.
- Canento, F., Lourenço, A., Silva, H., Fred, A., and Raposo, N. (2013). On real time ECG algorithms for biometric applications. In *Proceedings of the 6th Conference on Bio-Inspired Systems and Signal Processing (BIOSIGNALS)*.
- Carreiras, C., Aidos, H., Silva, H., and Fred, A. (2013). Exploratory eeg analysis using clustering and phase-locking factor. In *Proceedings of the 6th Conference on Bio-Inspired Systems and Signal Processing (BIOSIGNALS 2013)*.
- Coan, J. A. and Allen, J. J. (2007). *Handbook of emotion elicitation and assessment*. Oxford University Press, USA.
- Dom, B. E. (2001). An information-theoretic external cluster-validity measure. Technical Report IBM Research Report RJ 10219, IBM Research Report.
- Duarte, F., Duarte, J., Fred, A., and Rodrigues, M. (2011). Average cluster consistency for cluster ensemble selection. In Fred, A., Dietz, J., Liu, K., and Filipe, J., editors, *Knowledge Discovery, Knowledge Engineering and Knowledge Management*, volume 128 of *Communications in Computer and Information Science*, pages 133–148. Springer Berlin Heidelberg.
- Dubes, R. and Jain, A. (1979). Validity studies in clustering methodologies. *Pattern Recognition*, 11:235–254.
- Engelse, W. A. H. and Zeelenberg, C. (1979). A single scan algorithm for QRS-detection and feature extraction. *Computers in Cardiology*, 6:37–42.
- Epp, C., Lippold, M., and Mandryk, R. L. (2011). Identifying emotional states using keystroke dynamics. In *Proceedings of the 2011 annual conference on Human factors in computing systems*, pages 715–724. ACM.
- Fairclough, S. H. (2009). Fundamentals of physiological computing. *Interacting with computers*, 21(1):133–145.
- Fowlkes, E. B. and Mallows, C. L. (1983). A method for comparing two hierarchical clusterings. *Journal of the American Statistical Association*, 78(383):553–569.
- Fred, A. (2001). Finding consistent clusters in data partitions. In *Proceedings of the Second International Workshop on Multiple Classifier Systems*, pages 309–318, London, UK. Springer-Verlag.
- Fred, A. and Jain, A. (2002). Evidence accumulation clustering based on the k-means algorithm. *Structural, syntactic, and statistical pattern recognition*, pages 303–333.
- Fred, A. and Jain, A. K. (2005). Combining multiple clustering using evidence accumulation. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 27(6):835–850.
- Fred, A. and Leitão, J. (2003). A new cluster isolation criterion based on dissimilarity increments. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 25(8):944–958.
- Fulton, J. (1999). *Mensa book of total genius*. Barnes & Noble Books.
- Gamboa, H., Silva, H., and Fred, A. (2007). HiMotion Project. Technical report, Instituto Superior Técnico, Lisbon, Portugal.
- Ghosh, J. and Acharya, A. (2011). Cluster ensembles. *WIREs Data Mining and Knowledge Discovery*, 1(4):305–315.
- Halkidi, M., Batistakis, Y., and Vazirgiannis, M. (2001). On clustering validation techniques. *Journal of Intelligent Information Systems*, 17:107–145.
- Jain, A. K. and Dubes, R. C. (1988). *Algorithms for clustering data*. Prentice-Hall, Inc., Upper Saddle River, NJ, USA.
- Kuncheva, L. I. and Vetrov, D. P. (2006). Evaluation of stability of k-means cluster ensembles with respect to random initialization. *IEEE Trans. Pattern Anal. Mach. Intell.*, 28(11):1798–1808.
- Levenson, R. W. (1992). Autonomic nervous system differences among emotions. *Psychological science*, 3(1):23–27.
- Lourenço, A., Rota Bulò, S., Rebagliati, N., Figueiredo, M., Fred, A., and Pelillo, M. (2013). Probabilistic

- evidence accumulation for clustering ensembles. In *Proc Int. Conf. on Pattern Recognition Applications and Methods (ICPRAM)*.
- Lourenço, A., Fred, A., and Jain, A. K. (2010). On the scalability of Evidence Accumulation Clustering. In *Proc. 20th International Conference on Pattern Recognition (ICPR)*, Istanbul Turkey.
- Luo, P., Xiong, H., Zhan, G., Wu, J., and Shi, Z. (2009). Information-theoretic distance measures for clustering validation: Generalization and normalization. *IEEE Trans. on Knowl. and Data Eng.*, 21(9):1249–1262.
- Mak, J. N. and Wolpaw, J. R. (2009). Clinical applications of brain-computer interfaces: current state and future prospects. *IEEE Reviews in Biomedical Engineering*, 2:187–199.
- Malmivuo, J. and Plonsey, R. (1995). *Bioelectromagnetism: Principles and Applications of Bioelectric and Bio-magnetic Fields*. Oxford University Press, USA.
- Medina, L. (2009). Identification of stress states from ECG signals using unsupervised learning methods. Master's thesis, Universidade Técnica de Lisboa, Instituto Superior Técnico.
- Meilã, M. (2007). Comparing clusterings—an information based distance. *J. Multivar. Anal.*, 98(5):873–895.
- Murray, I. R. and Arnott, J. L. (1993). Toward the simulation of emotion in synthetic speech: A review of the literature on human vocal emotion. *The Journal of the Acoustical Society of America*, 93:1097.
- Pell, M. D., Jaywant, A., Monetta, L., and Kotz, S. A. (2011). Emotional speech processing: disentangling the effects of prosody and semantic cues. *Cognition & Emotion*, 25(5):834–853.
- Pfurtscheller, G. and Lopes da Silva, F. H. (1999). Event-related EEG/MEG synchronization and desynchronization: basic principles. *Clinical Neurophysiology*, 110:1842 – 1857.
- Rand, W. M. (1971). Objective criteria for the evaluation of clustering methods. *Journal of the American Statistical Association*, 66(336):pp. 846–850.
- Silva, H., Fred, A., Eusebio, S., Torrado, M., and Ouakinin, S. (2012). Feature extraction for psychophysiological load assessment in unconstrained scenarios. In *Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 4784–4787. IEEE.
- Silva, H., Lourenço, A., Lourenço, R., Leite, P., Coutinho, D., and Fred, A. (2011). Study and evaluation of a single differential sensor design based on electro-textile electrodes for ECG biometrics applications. In *Proceedings of the IEEE Sensors Conference*.
- Theodoridis, S. and Koutroumbas, K. (1999). *Pattern recognition*. Academic Press.
- Vega-Pons, S. and Ruiz-Shulcloper, J. (2011). A survey of clustering ensemble algorithms. *International Journal of Pattern Recognition and Artificial Intelligence (IJPRAI)*, 25(3):337–372.
- Wallace, D. L. (1983). A method for comparing two hierarchical clusterings: Comment. *Journal of the American Statistical Association*, 78(383):pp. 569–576.
- Zheng, W., Zhou, X., Zou, C., and Zhao, L. (2006). Facial expression recognition using kernel canonical correlation analysis (kcca). *IEEE Transactions on Neural Networks*, 17(1):233–238.