The Use of Electroencephalogram and Electrodermal Signals in Reinforcement Learning of a Brain-Computer Interface

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Abstract: The objective of this work is to compare the performance of two brain-computer interfaces developed by our research group. Both interfaces collect the electrical signals produced by the human body while a person try to move a cursor on a digital screen, using only his thought. The collected signals are classified using the artificial neural networks paradigm, where the first interface uses electroencephalogram signals, collected from the scalp, to classify the mental command, and the second uses the electrodermal signal, collected from any right-hand finger. Besides analysing the performance of the two approaches, this research contributes to reduce the training time achieved by similar systems, reported in the literature as being in an average of 45 days, to about only 40 minutes. Our motivation is to facilitate the accessibility of people with temporary or permanent physical limitations. In addition, we have developed a low-cost signal collection platform, providing a solution that can help a large group of people.

1 INTRODUCTION

The limbic system has an important role in controlling the human emotions such as motivation, stress and rage (Boucsein, 2012a). The limbic system integrates the sensory information from the environment with the emotional state, where an affective value is attributed to these stimuli, such as fear or pleasure. A positive feedback signal is sent for each action or intention of action performed correctly, resulting in the reinforcement of some synapses. In the other hand, wrong actions or intentions are discouraged by a similar mechanism (Amaral, 2016), (Nishida, 20126). In summary, the limbic system generates a signal of approval or rejection for every action we take, allowing a person to distinguish among what he likes or dislikes.

Although the limbic lobe is located in the inner part of the brain, from where it is very difficult to collect signals through an electroencephalogram (EEG), this system also controls the electrodermal (EDA) response, which is the electrical signal present on the skin and its glands. The EDA phenomenon is spontaneous and results from changes induced by a complex system of elements with different electrophysical properties. Moreover, the skin can be modeled by a set of resistors and capacitors, in relatively simple way, the EDA system can be a fast, low cost and low stress training method for brain-computer interface (BCI) applications (Boucsein, 2012a), (Blain, 2008).

On the other hand, another important brain interface is the EEG, whose responses are stationary in nature and vary at each recording session. The procedure for collecting EEG signals uses external electrodes and it is safe, inexpensive, non-invasive, with a satisfactory time resolution for most BCI studies and applications (Leskov, 2000), (Iacoviello, 2015). The captured signals are a composition of many electrical signals emitted by the human body, which means that some unwanted signals may be captured too. Fortunately, those useless signals can be easily eliminated through specific filters (Noteboom, 2001).

Applications based on EEG signals could allow an interaction between the environment and people, translating their imaginary movements into electrical signals. The construction of a limbic signal translator

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system can provide a wide range of home automation applications, such as control systems for switching electric household appliances, or for similar use in hospitals.

In some researches, the BCI system has proven to be a promising tool for applications that help people with severe motor limitations and for the implementation of remote medical devices (Lin, 2016) (Boucsein, 2012a). Based on these premises, our work aims to reduce the training time needed to customize the translation of the limbic signal to people with limitations in their motor capacities, whether temporary or permanent. This can be useful in situations where a person cannot wait a long time until he can start using such a system, as during a hospital stay.

The paper is organized as follows. In section 2 we present the state art of approaches for modeling of control system based on brain signals in BCI applications. Section 3 provides a description of our control system and the steps of the developed algorithm since collecting the signals until the final movement of the cursor on the screen. Subsequently, in section 4 we conclude with a discussion of our results. Finally, section 5 describe future research directions.

2 MODELING OF CONTROL SYSTEM

2.1 Electrodermal Activity

It has already been proven that the EDA signal (also known as galvanic skin response) can be used in BCI applications (Blain, 2008). We can consider the skin as a set of resistors and capacitors, where the glands are represented by a voltage source or by charged capacitors. In 1966, Montazu and Coles (Nishida, 2016) proposed an electric model of the skin, which can be represented by (1):

$$dR_{tot} = \frac{{R_2}^2}{(R_2+R_1)^2} dR \tag{1}$$

In (1), resistor R1 represents the equivalent resistance located in the dermis, resistor R2 models the resistance of the outermost layer of the skin, and resistance Rtot models the value of all sweat glands.
It has already been found that many lesions of the spinal cord do not prevent the EDA signal from remaining present. In individuals with lesions below T8, the EDA signal can be detected in both hands and feet, but for lesions between T4 and T8, the signal is only present in the hands (Boucsein, 2012b).

2.2 Electroencephalogram Signals

We detected the EEG signals based on the international system 10-20, which divides the skull into 21 points (Plonsey, 1995). The signals captured by the EEG are composed by brain signals combined with several other electrical signals emitted by the human body. However, we are only interested in the signals that reflect the intentions of the user and we need to eliminate everything that is considered as noise. For the procedure of signal filtering, we choose the discrete Fourier transform (Najarian, 2006).

2.3 The M Wave

The 8-12 hz wave and 12-30 (beta waves) are directly related to the motor regions of the cerebral cortex, what give them a great potential in BCI applications (Zhao, 2015). The main advantages of using μ waves are their capability of training a user to control the amplitude of these waves, and the fact that the muscular movements cannot interfere in the amplitude of these waves.

Wolpaw (1991) has already shown that a person can be trained to use the brain waves of 8-12hz to move a one-dimensional cursor. The author has developed a system in which a user moves a cursor vertically to reach a moving target. Five volunteers participated in an experiment that collected the signals with frequency of 3hz and subdivided their amplitude into 5 bands of μV. The amplitude of the collected signal is used to proportionally increase or decrease the size of the cursor offset. However, despite achieving a success rate of almost 90%, the training time for correct use of μ waves was up to three months.

Jun (Jun, 2015) collected μ waves from the two cerebral hemispheres and considered them as binary data, combined two by two, forming six different combinations. Each combination is used to identify commands that activate a mechanical arm (Jun, 2015).

3 MATERIAL AND METHODS

The purpose of this paper is to classify the electrical signals emitted by the brain and use then to vertically move a cursor on a digital screen. Two types of electrical signals were analysed to evaluate which one has the best performance in the purposed task. In both, an ANN is used to classify the signal and to decide whether the cursor should go up or down.

In the experiment using EEG signals, these are collected according to the international 10-20 mapping system, which specifies that the electrodes should be attached to the C3 or C4 positions of the skull (Figure 1).

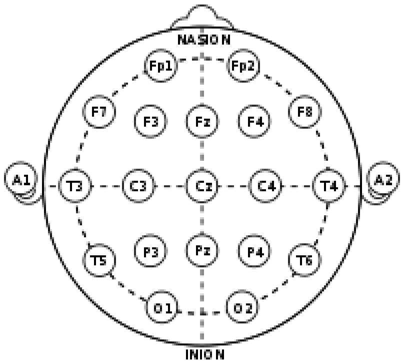

Figure 1: The international 10-20 mapping system of the skull (Wikipedia, 2018).

During the initial testing phase, we verified the need for signal amplification and filtering. So, we opted for the Chebychev bandpass filter and shielded the circuit to eliminate the noises, including those generated by electrical installations.

The collected signal was analog but we discretized in the frequency domain. For the discretization, we opted for the discrete Fourier transform, obeying the Nyquist criterion, where the sampling frequency must be at least twice as high as the highest frequency present in the original signal (Oliveira, 2017).

In the experiment using EDA signals, they can be collected through any hand finger (Plonsey, 1995), (Spliter, 2006).

3.1 Data Treatment and Analysis

Our experiments have shown that feelings of frustration, anxiety and nervousness decrease the amplitude of the EDA signal, while feelings of surprise and satisfaction increase their amplitude. In both cases, this variation is almost instantaneous, occurring soon after the generation of the pulse. After this change, the signal converges slowly to its base value.

At the first step of the EDA experiment, we generate labelled samples of each type of signal to obtain a set of data for the ANN's training phase. The samples are built by classifying each collected signal as neutral, frustration or surprise (when the cursor did not move, move in the wrong direction or move in the correct direction, respectively). The EEG experiment was conducted in a similar way.

For the signal collection, an intermittent message is positioned at the top or bottom of the screen, alternately, and the volunteer should try to move the cursor to the indicated direction, using only his thought. Each collection set results in 200 samples, divided between 100 thoughts of rise and 100 of descent.

After performing a relevance analysis of each frequency collected, in each type of signal, the frequencies of 8, 10, 12, 16, 18 and 20hz were selected for the two types of signal (EDA and |EEG), where the 10 and 12hz are the best all, since they are found within the spectrum of waves μ.

For the ANN, we chose a backpropagation MLP, a model that is proven to be suitable for pattern recognition problems. We tested different combinations of neural network parameters and architectures, where each configuration was tested 50 times. The model with the best performance was a 4-2-1 network, using a quasi-Newton Broydon-Fletcher-Goldfarb-Shanno (BFGS) function method to calculate the minima of a multi-variable objective function (Mathworks, 2016), learning rate of 0.6 and momentum rate of 0.9. The network inputs were the frequencies 8, 10, 12, 16, 18 and 20hz and the output was set to 0 (for down moves) or 1 (for up movements). For each individual training conducted, samples were randomly separated at a rate of 80% for training and 20% for testing.

For both signal type (EEG and EAD), the necessary steps, from collecting the signals to the final movement of the cursor on the screen, can be summarized by the following algorithm:

1. System training: an initial collection of signals is conducted and each of them is stored with its classification, UP or DOWN. At this stage, the cursor does not move, and the goal is only to generate a personal signal pattern for the user.
2. Training of an initial neural network RNA0: using the labelled signal samples generated in phase 1, and neural network with the architecture and parameters defined as explained in section 3.1, the goal is to train a personalized network for the user. Fifty complete trainings were performed in the neural network RNA0 to select the one that presented the best performance, using a class separation threshold of 0.5.
3. Collection of signal: A new collect occurs and now each of them will be classified by the

RNA0 and the cursor will be moved accordingly.

4. Training of neural network RNA1: Training of a new neural network, RNA1, using the signals generated in phase 3, with the same architecture, parameters and class separation threshold of RNA0, to provide an updated network for the user, assuming that his ability should have improved after the initial experiment. Again, 50 complete trainings were performed in RNA1 to select the best performance one.
5. Steps 3 and 4 are repeated twice until the RNA3 is trained, which corresponds to four test cycles.

4 RESULTS AND DISCUSSION

The experiment lasts, on average, 35 minutes and Table 1 shows the performance obtained at each step of the algorithm, for the EEG signal. From its analysis, we can verify that the best performance is found at step 2, when RNA1 is used to classify the second set of signals, and after that it tends to decrease. We can explain this by the intrinsic characteristics of the experiment, which caused a certain mental fatigue to all volunteers. In special, for volunteers 3 and 7 the performance of RNA3 was lower than RNA0, maybe reflecting their state of tension, who were visibly worried through all the experiment. A similar experiment, using the previous algorithm, but the EDA signal instead of EEG, was conducted and the results are shown in Table 2.

In Figure 2, we show the distribution curves of the EEG signals collect at each phase of the experiment, from volunteer #3. From the analysis of these graphs, we can see that the distributions of the two types of mental commands are indeed distinct, especially during the first and the second phases. After that, the performance begins to fall, as shown by the greater approximation between the curves, increasing the area of confusion between the signal patterns.

In Figure 3, we show the distribution curves of the EDA signals collected in each phase of the experiment, from the volunteer # 5. Differently from the distribution of EEG signals, the EAD distributions show that, for this type of signal, the performance continues to improve as new trainings are conducted.

Table 1: EEG recognition performance during the training phase of the neural networks.

Volunteer	%Hints of ANN_0	%Hints of ANN_1	%Hints of ANN_2	%Hints of ANN_3
1	56.52	78.26	69.57	60.87
2	73.91	78.26	82.61	73.91
3	60.87	78.26	65.22	73.91
4	60.87	65.22	86.96	78.26
5	65.22	65.22	82.61	73.91
6	69.57	73.91	60.87	78.26
7	73.91	73.91	82.61	78.26
8	73.91	69.57	78.26	78.26

Table 2: EDA recognition performance during the training phase of the neural networks.

Volunteer	%Hints of ANN_0	%Hints of ANN_1	%Hints of ANN_2	%Hints of ANN_3
1	78.94	78.94	47.37	78.95
2	73.68	63.16	63.16	84.21
3	63.16	89.47	84.21	78.95
4	65.52	65.52	82.76	65.52
5	62.07	75.86	82.76	100
6	84.21	73.68	78.95	78.95
7	82.36	85.29	70.59	67.65
8	61.76	82.35	82.35	85.29

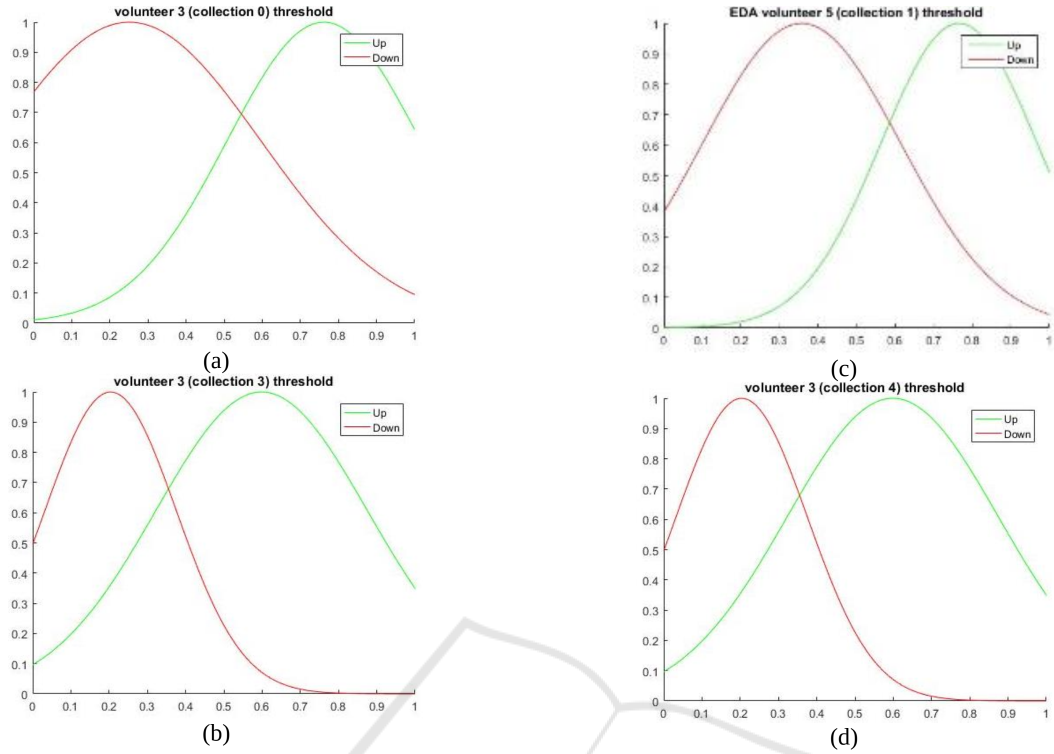

Figure 2. Distribution of EEG signals for the thoughts of rise (green) and fall (red) of volunteer #3.

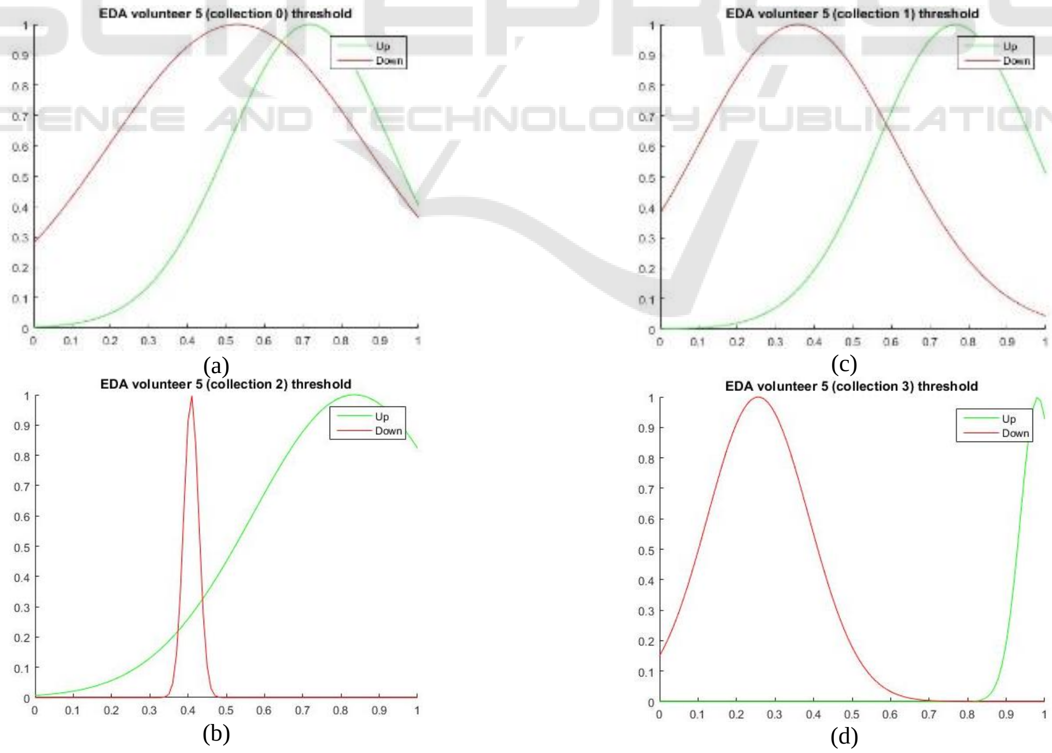

Figure 3: Distribution of EDA signals for the thoughts of rise (green) and fall (red) of volunteer #5.

5 FUTURE WORK

The EDA signal is controlled by the limbic system (Fausett, 1994), which also generates the approval and disapproval responses, defining our choices and actions (Boucsein, 2012b). Proper modelling of this behaviour can generate interesting solutions for people with such severe physical limitations that they cannot express their needs and feelings. Since the electronic circuit used in this work has a low cost, the use of EDA can, more quickly than conventional BCI using EEG, generate solutions that reach a larger part of the population.

Other studies found in the literature related the use of the EDA signal to correct the commands generated by the EEG signal (Boucsein, 2012a), but we have shown in this work that the training time of a BCI application can be reduced by using the EDA signal instead of the EEG. In addition, the technology developed by our research group, which included the design and development of a custom acquisition circuit, can reduce the cost of this type of BCI application, opening possibilities for its use in other fields of research. While a wifi EEG headset plus electrodes could cost almost U$800.00, an EDA detector can be bought by only U$10.00.

The choice for the ANN paradigm for signal recognition was also a good decision. As we predefine the network architecture and training parameters, and parameterize the training process, potential users of our BCI system do not need any technical knowledge to learn how to use it.

For a future work, it will be interesting to explore the limits of the EDA signal applied to BCI, such as collecting EDA signals from more than one region, for example, from the right and left hand at the same time. The combination of these signals could increase the variety of responses and, consequently, the number of possible BCI applications. Tsukahana (2002) presents another approach for electrodermal signal codification, generating more than one binary signal to increase the choices of movements for the user.

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