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EEG-based person identification through Binary Flower Pollination Algorithm

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ABSTRACT

Electroencephalogram (EEG) signal presents a great potential for highly secure biometric systems due to its characteristics of universality, uniqueness, and natural robustness to spoofing attacks. EEG signals are measured by sensors placed in various positions of a person's head (channels). In this work, we address the problem of reducing the number of required sensors while maintaining a comparable performance. We evaluated a binary version of the Flower Pollination Algorithm under different transfer functions to select the best subset of channels that maximizes the accuracy, which is measured by means of the Optimum-Path Forest classifier. The experimental results show the proposed approach can make use of less than a half of the number of sensors while maintaining recognition rates up to 87%, which is crucial towards the effective use of EEG in biometric applications.

1. Introduction

In modern life, we constantly make use of passwords to access our bank accounts, e-mail boxes, and social networks, just to name a few. As passwords can be easily circumvented, the use of biometrics has been proposed for safe person identification (Jain, Ross, & Nandakumar, 2011). Over the years, the use of biometric systems has increased, and systems based on several biometric modalities such as fingerprint, face and iris, have been successfully deployed. This successful and widespread deployment of biometric systems brings on a new challenge: spoofing. Spoofing methods are developed to breach the security of biometric systems so that unauthorized users can gain access to places and/or information (e.g., an artificial finger made from silicone is placed on the fingerprint scanner).

In this scenario, the EEG (electroencephalogram) signal presents a great potential for highly secure biometric-based person identification, due to its characteristics of universality, uniqueness, and robustness to spoofing attacks (Beijsterveldt & Boomsma, 1994). It is well-known the importance of EEG signals in several areas, since one can find a number of works that deal with such a source of data (Guo, Rivero, Dorado, Munteanu, & Pazos, 2011; Nunes, Coelho, Lima, Papa, & Albuquerque, 2014; Ocak, 2009; Subasi, 2007). In high security environments, EEG sensors can be integrated in order to contribute to the robustness of the system, and the person can be continuously authenticated. Although the idea of using EEG as a biometric trait is not new, there are a few works that address such kind of signal only. One possible explanation for that is the difficulty in obtaining such signals, and also because the biometric characteristics of the EEG signal may be held only for short periods of time (Pollock, Schneider, & Lyness, 1991).

With the emergence of new mobile devices that capture brain signals driven by the most keenly studies in the brain computer interface, the EEG as a biometric trait can now be used in some other scenarios, such as: (i) distance-based education environments, in which the continuous authentication of a student becomes increasingly necessary; (ii) with the increase in life expectancy worldwide, health monitoring systems may become popular along with home automation and smart homes, thus making the EEG-based identification very useful in this scenario; (iii) with the popularization of biometric systems for the validation of financial transactions, mobile EEG sensors become a viable alternative in the future.

Basically, an EEG-based biometric approach aims at placing a set of sensors in the person's head in order to capture the output signals for further feature extraction and analysis using signal

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processing techniques. The signal acquisition session is then repeated over time to make the system more discriminative and robust to errors. In a recent paper, (Campisi & La Rocca, 2014) presented a review on the state-of-the-art of EEG-based automatic recognition systems, as well as an overview of the neurophysiological basis that constitutes the foundations on which EEG biometric systems can be built. The authors also discussed about the major obstacles towards the deployment of EEG based biometric systems in everyday life.

One of the main problems of EEG-based person identification is the acquisition, which may be too invasive to the user. The process of putting a considerable amount of sensors up on a person's head might be a bit uncomfortable, and it also requires a previous knowledge by the person in charge of the sensors placement in order to put them in their correct positions. In light of this context, some questions may rise: "Is it really necessary to put all these sensors on a persons' head? If not, can we identify the most relevant channels for person identification and then use a smaller number of sensors in order to measure them?".

These questions motivated our work in modelling the task of channel selection as an evolutionary-based optimization problem. The idea is to propose a wrapper approach composed by an optimization technique and a pattern classifier, in which the accuracy of the latter is used to guide the evolutionary agents in the search space looking for the best solutions, i.e., the subset of channels that maximize the accuracy of the classifier in the validation set. Any optimization technique and classifier could be used.

In our work, we propose an optimum channel selection by means of a binary constrained version of the recently proposed optimization technique Flower Pollination Algorithm (BFPA) (Yang, 2012), and the Optimum-Path Forest (OPF) (Papa, Falcão, Albuquerque, & Tavares, 2012; Papa, Falcão, & Suzuki, 2009) classifier, which is a supervised pattern recognition technique that has the advantage of providing a faster training phase compared to other state-of-the-art classifiers. This characteristic of fast training is very important in the context of this paper, since a training procedure followed by a classification of a validation set need to be performed for each evolutionary agent (sometimes we may have several of them). Additionally, this version of OPF is parameterless, which is another advantage over other classifiers.

The main contributions of this paper are three-fold: (i) to evaluate a recent binary version of the Flower Pollination Algorithm (BFPA) proposed by Rodrigues, Yang, Souza, and Papa (2015) under different transfer functions[1]; (ii) to model the problem of EEG channel selection as an evolutionary-based optimization task; and (iii) to introduce the OPF classifier for EEG-based biometric person identification. The use of evolutionary optimization algorithms for the EEG channel selection is due to their elegant and simple solutions to solve optimization problems, similar to the way nature does.

This paper is organized as follows: Section 2 presents a brief theoretical background about EEG, and Section 3 discusses previous works related to this paper. Section 4 presents the proposed approach for person identification using a reduced number of EEG channels, and Section 5 presents a description of the dataset and the experimental setup. Sections 6 and 7 discuss the experiments and conclusions, respectively.

2. The EEG signal

The human central nervous system consists of the encephalous (brain), which is inside the cranium, and the spinal cord contained in the spine. The nerve tissue is a complex network formed mostly by millions of nerve cells (glial cells and neurons), whose primary function is the transmission of electrical impulses that run through this intrinsic and huge network, thus propagating information among cells (Sanei & Chambers, 2007; Tau & Peterson, 2009). These small electrical impulses emitted by the huge amount of neurons create an electric field that can be measured on the surface of the human skull, with the help of sensors or electrodes. The measurement of this complex electrical signal from our nervous system is what is known as electroencephalogram (EEG). In the literature, it is common among authors to directly refer to those brain waves as EEG.

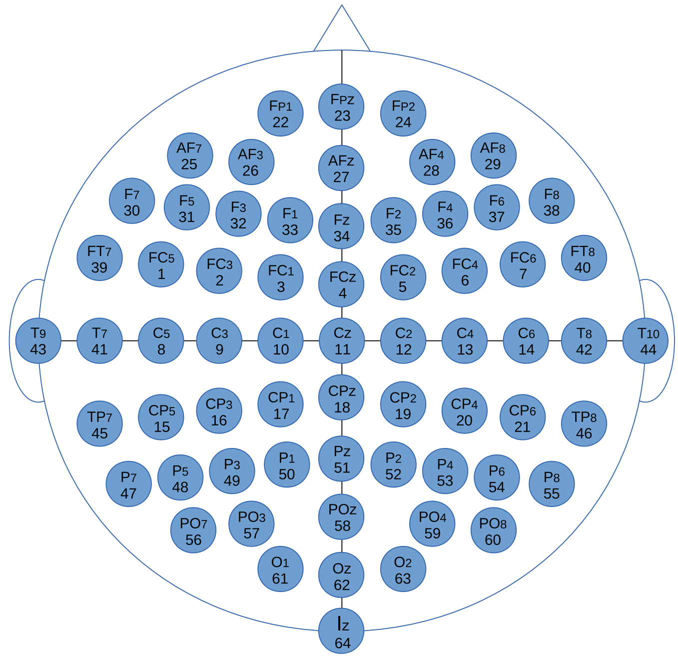

Fig. 1. International 10-10 System standards for sensor positioning. Just for the sake of clarification, sensor T9 is placed close to the left ear, as well as sensor #23 is placed close to the nose.

The neural activity of the human being begins between the 17th and 23rd week of gestation. It is believed that, since this stage, and throughout the life, the signals from the brain activity represent not only the functioning of the brain, but also of the whole body. Published studies also show that even if a variation in amplitude of EEG signals during the development of a normal person exists, over the years, their functional connections remain largely unchanged (Gasser, Jennen-Steinmetz, Sroka, Verleger, & Macks, 1988; Tau & Peterson, 2009).

Fig. 1 shows an example of a map of sensors located at a person's head. This map describes the head surface locations via relational distances, also called as International 10-10 System (Jurcak, Tsuzuki, & Dan, 2007; Nuwer et al., 1998). The nomenclature of the electrodes is associated to the human brain areas as follows: Frontal (F), Central (C), Temporal (T), Parietal (P) and Occipital (O) lobes. Electrodes named with two letters refer to a location between areas, for example: CP electrode is in a position between central and parietal lobes. The sub-index indicates the side of the brain hemisphere (odd numbers are located on the left side and even numbers on the right side), and the sub-index "z" indicates that the electrode is located in the main vertical axis.

3. Related work

One of the first studies regarding EEG as a biometric trait was conducted by Poulos, Rangoussi, Chrissikopoulos, and Evangelou (1999), which described the EEG signal by means of an autoregressive (AR) model as the basis for a person identification method. In

[1] A transfer function, in this context, aims at mapping a real-valued solution to a binary-valued one.