Machine Learning and EEG based Biometrics (MLE)

Dimosthenis Karafylias[1]

Abstract:

The approach of analyzing brain electroencephalography (EEG) signals for human identification has recently become a popular modality in the biometrics world. The electrical activity of the brain, in a broad sense, has been studied for a longer time in the context of cognitive neuroscience. This scientific domain examines the nature and the function of cognition. It was recently though, that it was discovered that brain activity could offer confidentiality, resistance to spoofing, sensitivity to emotional and mental state due to its uniqueness. These traits render the study of EEG based biometrics a promising one. In addition, several studies advocate that this method could emerge to be fairly robust and secure. This comprehensive report aims to examine if this is actually the case, at least for the most part of the literature and to cover the relation between machine learning and EEG based biometrics, the advantages, disadvantages, challenges and evaluation of different scientific approaches as well as practicalities about the way the brain signals could be captured and used for identification and authentication.

Keywords: Biometrics, Electroencephalography, EEG, Brain, Identification, Authentication, Machine Learning

1 Introduction

Means of authentication and identification can be classified into three groups: something the user knows, something the user has, and something the user is. As something the user knows, passwords and physical debit cards, gradually become less secure verification methods. They can be forgotten or lost. Thus, biometrics have emerged the last years and are widely adopted in a variety of everyday applications. After a short introduction on biometrics' generic definition, the rest of the report keeps its focus on a particular method (i.e. EEG) and is organized in concise and clear sections which describe the characteristics, steps to identification and authentication, evaluation of different approaches and finally suggestions for future improvements.

1.1 Biometrics

Biometrics refer to human characteristics which are used to identify and authenticate individuals. Examples that have not only been studied in literature in depth, but also adopted in real-life applications include fingerprint, veins, face recognition, DNA and iris recognition. For the purposes of this report, the previous methods are considered only as means of

[1] DTU Compute, Department of Applied Mathematics and Computer Science, Richard Petersens Plads, Building 324, DK-2800 Kgs. Lyngby, s202632@student.dtu.dk

comparison and are not independently reviewed. In the literature, they are widely considered to be more efficient and and secure than traditionally used methods such as passwords. Nonetheless, with the advancement of imitation technologies, these conventional biometrics, have some constraints. For example, it is possible to copy a fingerprint using silicone or even a photograph. Apple's 2013 touch ID was hacked by capturing a high-resolution photo of the latent fingerprint on the glass touch screen. Similarly, a face or iris could be imitated using a replicated, high quality photograph of the subject. In addition, iris, face and fingerprints are considered to be noncancelable. If stolen or forged by a third party, a user cannot replace them. According to the findings of this study [GHB18], fingerprint image quality decreases linearly with age, after 40-45 years of age. Therefore, this poses another difficulty. Elderly, might not be able to participate in social and cultural life, in a broad sense, and may not have the ability to access the services available to everyone else [GHB18].

Given the risk of intrusiveness, research on alternative biometrics has been motivated. The direction is clearly towards a biometric more secure, more difficult to steal and cancelable. A biometric using Electroencephalography (EEG) and brain electrical activity might be able to meet these criteria. It provides a more secure system as it is not easy to be faked or obtained forcefully. There is no way to replicate others' brain signals, at least with the current technology [Ch19].

1.2 EEG

As a short introduction to the core issues, it would be useful to discuss some important attributes of Electroencephalography (EEG) as a method which records electrical activity on the scalp. EEG is typically non-invasive and involves placing electrodes around the scalp to measure voltage generated from the neurons of the brain. Advantages of EEG over other known methods which study the brain function, such as Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET), include lower hardware costs, tolerance to the movement of the subject [ORFM10], non-invasive measurements (electrodes around the scalp), mobility and size of the equipment [Hä93], stability over different phases of life, nonnecessity of the subject to attend to stimuli.

On the contrary, EEG cannot successfully capture all neural activity from the lower brain layers (e.g. cortex) and has a poor signal-to-noise ratio, meaning that a relatively large data set is required for obtaining useful insights. Lastly, EEG usually needs a longer preparation time than other methods. The placement of the electrodes should be precise and there is also a requirement to use specific adhesive pastes or rich in electrolytes gels for better conductivity.

1.3 EEG characteristics

Brain biometrics can only be captured when the user is alive and in a conscious state [Sa15]. Electrodes must be placed around the scalp to collect the brain activity. Measurements cannot be made from a distance and thus this method ensures that electrical activity will not be captured and stored without consent. What is also worth mentioning, is that EEG measurements are very sensitive to mental state. Any stimuli that would stress the subject, could also alternate the brain activity and influence the measurements. Consequently, a user cannot be forced to authenticate and identify themself, under stress [CJ08]. As an identification and authentication method, EEG could be used in cases that require a high level of security, such as military data and facilities or financial data and resources.

Interesting facts about the EEG signal worth noting are: (i) EEG is neither a fully deterministic, nor a stochastic signal. It would be difficult to invent new things and conversely, difficult to repeat things already learned. (ii) 3-N principle: EEG signals are essentially non-stationary (frequency changes with time), non-linear and noisy [Kl09].

2 Steps to identification and authentication

Usually the process of identification and authentication, as described in the literature, has four steps to be completed, namely the EEG measurement, a filtering step to filter out the noise, a feature extraction step to decompose the signal (e.g. in frequency sub-bands) and the final step of classification in which the signal is compared to the existing one in the database and is given a matching score.

2.1 EEG signal collection

Brain electrical activity can be captured when the subject is (i) relaxed and has closed eyes, (ii) exposed to visual stimulants and (iii) performing mental tasks. In the first and more simple one of these methods the participant is at rest state during the experiment. This is also the most common method. The two following ones are more complex. The second method usually involves stimulants in the form of images, such as human faces, or visualizations. In the third case, the literature reveals that there might be tasks such as object counting, mathematical computations, driving scenes in virtual environments, movements of hand, feet or tongue and recalling pictures.

Fig. 1: EPOC Flex Gel Sensor Kit
image source: `https://www.emotiv.com/product/epoc-flex-gel-sensor-kit`

This is a typical kit that includes a cap, electrodes and a conductive saline or Ag/AgCl+ gel. It is equipped with 32 electrodes capable of capturing brain electrical signals in the frequency range 0.16 - 43 Hz. As a study reveals, the EEG frequency bands are: delta

(1–3 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (13–30 Hz) and gamma (30–100 Hz). The boundaries of corresponding bands appear to be lower in infants and children [SM12].

2.2 Noise reduction and filtering

EEG signal is usually very contaminated when collected. Electrical equipment nearby as well as the movement of the eyes and face contribute to the overall SNR (Signal-to-Noise) ratio. A noise-reduction step is necessary to be applied in order to discard the frequencies that correspond to noise. In most cases, a band-pass FIR (finite impulse response) filter is applied (settles to zero in finite time). The filter has a lower cutoff frequency which ranges from 0.1 to 0.5 Hz and a higher one that usually ranges between 50 and 60 Hz. Other popular options that appear in the literature, are the low-pass filters and the higher order Butterworth filters. (The Butterworth filter rolls off slowly around the cutoff frequency but without having ripples. It is designed to have a flat frequency response.)

2.3 Feature extraction

Method	Pros	Cons
1. PCA (Principal component analysis)	Dimension reduction without losing data	Unable to process complicated set of data
2. ICA (Independent component analysis)	Computationally efficient, high performance for large data sets	Requires more computational power for decomposition
3. WT (Wavelet transform)	Suitable for non-stationary signals, able to analyze signal both in time and frequency domain	Lack of specific methodology to apply to pervasive noise
4. AR (Autoregressive)	Requires short duration of data, reduces spectral loss problems and gives better frequency resolution	Not applicable to stationary signals

Tab. 1: Pros and Cons of popular feature extraction methods
table source: [GONa19], p. 58

After filtering, the signal available, does not have any of the undesirable noise left. However, further refining is required. Particularly, the step of feature extraction is vital in order to authenticate or identify people most effectively. The quality of the extraction is directly responsible for the behavior of the recognition system. The feature extraction can be classified as (i) time domain, (ii) frequency domain and (iii) time-frequency domain and there are several approaches, as listed in the table 1, above. In their essence, these decomposition techniques are means of analyzing the signal in the frequency or time domain.

1. PCA, short for Principal Component Analysis, is a useful technique that essentially, transforms the data to a coordinate system such that the component with the greatest

variance lies on the first coordinate [Jo02]. PCA is used to remove noise, increase SNR (Signal-to-Noise) ratio and reconstruct the signal using the components with the greater variance [PR06].

2. ICA (Independent Component Analysis) is a method for decomposing a signal into non-Gaussian components. It has been shown that ICA can decompose multi channel EEG signals into different components and frequency bands [OM06].

3. WT (Wavelet Transform) is the most widely used approach and, in this case, could be considered as an alternative to the Fourier transform. Traditionally, Fourier is used for signal analysis within certain frequency. Nevertheless, it is not possible to analyze both in time and frequency with FT and, in addition, Fourier loses the time component from the signal, which is an important factor for extracting information. Along these lines, DWT (Discrete Wavelet Transform) was introduced and deemed useful for time-frequency analysis, as it captures both frequency and location information (location in time) [KV15]. DWT could be written as:

$$S_{2^i}x(n) = \sum_{k \in Z} h_k S_{2^{i-1}} x(n - 2^{i-1}k) \tag{1}$$

$$W_{2^i}x(n) = \sum_{k \in Z} g_k S_{2^{i-1}} x(n - 2^{i-1}k) \tag{2}$$

where S_{2^i} is a smoothing operator, W_{2^i} is a digital signal of $x(n)$, $i \in Z$ is the integral set, h_k is the coefficient of the low-pass filter and g_k the corresponding one of the high-pass filter.

A method more robust than DWT, is the Wavelet Packet Decomposition (WPD) where the signals pass through more filters than DWT and both the detail and approximation coefficients pass through the low and high pass filters, while in DWT, only the approximation coefficients pass through the filters. 'Detail' refer to the high pass filtered signals and 'approximation' to the low pass filtered ones. Wavelet Packet Transform uses signals of continuously changing frequency and gives both time and frequency representation of the signal, without altering the original one.

A wavelet transform, used frequently in the literature for EEG signal analysis, is the Daubechies. Daubechies are orthogonal wavelets that define discrete wavelet transforms and can extract statistical features such as mean, standard deviation, energy and entropy. In literature, they are usually referred to as dbN, where N denotes what is called the number of vanishing moments. The greater this number is, the more smooth the signal appears [Ed18]. Daubechies-4 (db4) is perhaps the most popular when working with EEGs because it can detect changes in these signals thanks to its smoothing feature [Su07].

4. AR (Autoregressive) is a random process model that analyses a signal in the time domain. It specifies that the output depends linearly on its own previous values and thus forming a stochastic equation that expresses each element as a function of the preceding element [Gu19].

It can be written as:

$$x(n) = -\sum_{i=1}^{p} a_i x(n-i) + e(n) \tag{3}$$

where a is the parameter of the model, n is the time, p is the order and $e(n)$ is white noise.

2.4 Signal Classification

Now that the most important components of the signal are already extracted and analyzed, classification checks and compares the signal with the existing one in the database and assigns a similarity score wherein the authentication depends upon. This is a critical point in the process and a step where machine learning methods become most apposite. This section demonstrates the most frequently used methods, as encountered during the time of writing. This list is not comprehensive and may have omitted either supervised or unsupervised learning architectures.

2.4.1 Artificial Neural Networks (ANN)

Neural networks are biologically inspired classification algorithms that typically have 3 layers, namely the input layer, the output layer and one layer called hidden. Layers are connected with edges or links, which carry a weight that constantly changes as the learning process continues. This weight directly influences the power of the signal from one layer to the next one. By adjusting the weights the accuracy of the model improves. This practically continues until these changes no longer reduce the error rate and thus learning is complete.

In most of the literature, the setup included an ANN class called MLP (Multi-layer Perceptron). It is in essence a feed-forward NN composed from at least 3 layers that uses the backpropagation algorithm. Backpropagation computes the gradient of the cost (or loss) function of the weights. It does so, backwards from the last layer and one layer at a time. A study found [Ba17], used a popular repository containing the Deep Learning Keras and Tensorflow 2 libraries, to create the MLP as a classifier [Ch]. This classifier achieved an accuracy of $84,69\%$ which was the highest one among other classifiers such as Support Vector Machine (SVM), Random Forests (RF) and AdaBoost (AB).

2.4.2 Support Vector Machine (SVM)

SVM is a binary classifier that maps data points in space and decides where each point belongs, out of two categories. In most cases, there is a distinctive line between the two categories, called hyperplane, that separates them. According to SVM the best separation between the categories would be a hyperplane placed in such way that maximizes the distance between the hyperplane and the closest point from each one of the two categories. SVM maximum margin hyperplane and Non-linear SVM algorithmic examples, both using the scikit-learn 0.24.2 library: [SV], [No]. The usage of non-linear kernels is also common. They certainly increase complexity but they achieve greater separability. RBF (Radial Basis Function) kernel, using squared Euclidean distances, is one of them [VTS04], [RB].

2.4.3 Linear Discriminant Analysis (LDA)

LDA is usually defined as a dimensionality reduction scheme. However, LDA can actually appear as a classifier in the literature which uses the familiar hyperplanes concept that performs binary classification. The very first idea of LDA, proposed by R. Fisher in 1988, was the maximization of the difference of the classes means while normalizing by a measure of the within class variability. This is proven to be more efficient under the assumption that the data distribution is Normal. According to the literature, LDA would be most suitable for classifying linearly separable data. The most commonly used approach of LDA would be the Quadratic Discriminant Analysis (QDA), which uses a quadratic decision boundary and Bayes' rule to find the optimal solution [Qu]. In case of non-linearity, models such as ANN or SVM with non-linear kernels are encouraged more.

2.4.4 k-Nearest Neighbors (kNN)

k-Nearest Neighbors' learning process is based on proximity. k indicates the number of nearest neighbors the classification is subject to. If $k = 1$ then the object is assigned to the same class of its single nearest neighbor. To calculate the distance, the most common metric is the Euclidean distance. According to the claims of this recent study [Ek21], higher k parameters yield better accuracy models by reducing noise in the classification process. Finding an optimal parameter k might need some research on its own. As a supervised learning algorithm, a confusion (or error) matrix is commonly used to visualize its performance.

2.4.5 Naive Bayes Model (NBM)

Naive Bayes is a probabilistic classifier based on the renowned Bayes theorem. The naivety refers to the attributes being strongly (naive) independent. Maximum likelihood, a special case of maximum a posteriori estimator (MAP) estimator is the probability model used to construct the classifier. To put it another way, the Bayes probability model must be integrated with a decision rule to build the classifier. For a vector $x_1, ..., x_n$ to be classified in a class the probability y is given by:

$$\hat{y} = \underset{y}{\operatorname{argmax}} P(y) \prod_{i=1}^{n} P(x_i|y) \tag{4}$$

According to this study [CNm06] the NBM algorithm performs more poorly as a classifier compared to Random Forests (RF), Support Vector Machine (SVM), Artificial Neural Networks (ANNs) and other commonly used algorithms over several different classification tasks.

2.4.6 Random Forests (RF)

Random Forests is a learning method based on decision trees. It selects random observations and variables to build multiple decision trees. Regarding classification tasks, the result is the output selected by the majority of the trees. Thus, the random forests' classification output is generally of higher accuracy than the one of decision trees. There is nevertheless, a special case of decision trees, using boosting, called Gradient Boosted Trees. If the parameters are carefully tuned, gradient boosting can result in better performance than RF. This recent study proposed an EEG-signal classification scheme, using gradient boosting decision trees (GBDT) and Wavelet Packet Decomposition (WPD) techniques, to decompose the EEG signals into frequency sub-bands and achieved an accuracy of $87,68\%$ [Al20]. It was slightly outperformed by a system using a combined AlexNet (convolutional neural network (CNN)) and MLP (Multi-layer Perceptron) architecture, which in turn achieved $89,13\%$ accuracy.

2.4.7 AdaBoost (AB)

AdaBoost is primarily used in combination with other algorithms in order to boost performance. The outputs of the other algorithms are combined into a weighted sum to eventually form the boosted classifier. Thus, in a sense, AdaBoost is similar to Random Forests, as they are both tree-based algorithms, with the difference that it builds decision trees as learners and punishes incorrectly predicted samples, by assigning a larger weight to them after each prediction. While it is a robust and computationally inexpensive algorithm, some studies argue that AB is susceptible to high noise data. This might be the reason why AB is not so frequently used in EEG signals classification systems.

2.4.8 Convolutional Neural Networks (CNNs)

Supervised learning algorithms have their advantages in brain biometrics. Their performance depends on manual tuning of specific features. Thus, the performance can be easily influenced. Taking into account the fact that EEG signals are noisy and random brain activities could influence certain features and in turn the performance of the model, considering unsupervised learning approaches that have already been successful in other domains, might be a promising alternative.

Convolutional Neural Networks, a family of deep learning variants, are such a paradigm to have already achieved that great success in the fields of image recognition and video analysis. Similarly to an MLP, they consist of an input layer, an output layer and multiple hidden layers. However, they have more hyperparameters than MLPs. Hidden layers, in turn, include layers that perform convolutions (i.e. convolutional), pooling layers (reducing dimensions), fully connected layers (same as MLP) and normalization layers. Then, network weights, change each time through the backpropagation algorithm which calculates the cost function's gradient in order to reduce the classification error [Wa19]. The same study ([Wa19]) classified EEG signals with CCNs, LDA, SVM and MLP and concluded that the CNN model had a better result when tested with 3 different subjects.

Other notable learning approaches may be the following ones: Gaussian Mixture Model (GMM), Hidden Markov Model (HMM), the Linear and Polynomial Classifier, Support Vector Data Description (SVDD) as well as other variants of Neural Networks such as Fuzzy and Elman NNs.

3 Evaluation

While the majority of the papers studied, disclose their findings and the accuracy of their models, it is not easy to decide on the best one. There exist cases where Random Forests (RF) performed better than Support Vector Machine (SVM) [GONa19], or conversely, RF being outperformed by SVM [Ba17]. There is no one-size-fits-all approach. Each problem is unique and needs its tailored technique. What is possible though, is to extrapolate some trends about the accuracy of the models, the feature extraction and classification methods.

The Wavelet Packet Decomposition (WPD) is perhaps the predominantly used feature extraction method. Daubechies-4 (db4) seems to be the most favorable of all, as it can detect changes in EEG signals due to its smoothing feature.

Among all classification methods, Support Vector Machine (SVM), Random Forests (RF), Linear Discriminant Analysis (LDA) and different variants of Neural Networks (NNs) are the most accurate and efficient. All of these models, as reported, achieved at least an 80% rate in their performance. The selection of the classification method is highly dependent on the training time, parameter tuning, duration of the EEG signal collection, the number of subjects (small datasets could suffer from overfitting), the tasks the subjects perform during EEG collection, measuring equipment and a few others. It is also very usual for a paper to feature a uniquely proposed classification method, that is specifically fit for a particular identification case. Nevertheless, there is a tendency lately for unsupervised learning and Convolutional Neural Networks (CNNs).

This recent study [Ch20] proposes a novel CNN called GSLT-CNN (Global Spatial and Local Temporal filter - Convolutional Neural Network) which works directly with EEG raw data and does not require a feature extraction method. The deep learning training software used was Tensorflow [Mab], while Matlab was used for the baseline classifiers [Maa]. When compared with other state of the art algorithms, GSLT-CNN achieved 96% accuracy on raw data, while LDA and SVM 31% and 75% respectively. On the contrary, using the PSD (Power Spectral Density) + SFFS (Sequential Forward Floating Search) as the feature extraction method, GSLT-CNN achieved 89%, LDA 63% and SVM 93%. Lastly, the Correct Recognition Rates (CRR): GSLT-CNN (raw data) $96,3\%$, SVM+PSD+SFFS $92,9\%$ and SVM+AR+SFFS $86,3\%$.

4 Challenges and future improvements

- EEG signal based biometrics is improving as a whole, yet, this method, still has unsolvable and challenging issues. Noisy data, similarities in input signals when the system is used by a large population, user movements while capturing the signals (usually lead to increased noise), EEG signals are susceptible to physiological and psychological conditions, to name a few. There is an observed trend for multimodal biometrics. These methods usually combine two different approaches to build an even more robust system. Generally, these fusions take place at the feature level. Multiple signals are firstly extracted and then concatenated together as a set before classification.

  This recent study [Ra21] proposes a combination of EEG and keystroke dynamics (pressing a password/pin on the keyboard). The system achieved $4,9\%$ more accurate identification rates than using EEG alone. This study [Ba19] proposes a fused EEG and ECG (Electrocardiography) classifier that outperforms ECG and EEG by approximately $24,51\%$ and $3,20\%$ respectively.
- Although brain biometrics are generally secure, modern cyberattacks may pose certain threats to the system's integrity. Hill-climbing attack is one of them. In this case, an attacker exploits the score produced by the matcher, to generate a synthetic EEG signal and gain unauthorized access. Various studies try to address this risk using unconstrained optimization algorithms such as Nelder-Mead [TM12], SPSA [Ma13] and Hooke-Jeeves [Ma13].

  In case of forced recognition, [Su12] suggests an authentication with warning signals. These would allow users to send warning signals along with the EEG ones. Even if EEG is authenticated the access could still be denied if the warning signals are successfully detected.
- Another security issue discussed, is the permanence of EEG signals along time, as this would question EEG based biometrics as an identifier. [MC18] concluded that EEG signals only slightly vary over time and suggested aging effect countermeasures that could render EEG more robust over time.
- EEG is very sensitive to mental states and stress. What is not so commonly known though, is that EEG is also influenced by diet and circadian rhythm. This study reports that a concurrent change in diet and time of measurements (circadian rhythm) may even lead to a 30% drop in identification accuracy [Su10].
- This study discusses the role of Machine Learning in biometric systems and lists some of the challenges [CL18]. A large data set to produce good models, noisy environments, time constraints, huge memory to store the database and need of continuous improvements for security reasons are some of the downsides. On the bright

side, ML is a constantly developing field that may overcome some of these difficulties in the near future.

5 Conclusion

This report is an attempt to describe current topics in EEG based Biometrics, different algorithms, challenges, models and methods, advantages and disadvantages that ultimately lead to the identification and authentication of individuals. The last part explored potential future work and improvements. Within the time constraints, most current literature was surveyed when possible, and the results were presented in a concise manner. As final thoughts, through own understanding, special care should be given to the feature extraction, classification methods and overall security, as they have a prominent role on the potential successful adaption of EEG based biometrics to everyday applications.

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