Shallow Neural Network for Biometrics from the ECG-WATCH

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Abstract. Applications such as surveillance, banking and healthcare deal with sensitive data whose confidentiality and integrity depends on accurate human recognition. In this sense, the crucial mechanism for performing an effective access control is *authentication*, which unequivocally yields user identity. In 2018, just in North America, around 445K identity thefts have been denounced. The most adopted strategy for automatic identity recognition uses a *secret* for encrypting and decrypting the authentication information. This approach works very well until the *secret* is kept safe. Electrocardiograms (ECGs) can be exploited for biometric purposes because both the physiological and geometrical differences in each human heart correspond to uniqueness in the ECG morphology. Compared with classical biometric techniques, e.g. fingerprints, ECG-based methods can definitely be considered a more reliable and safer way for user authentication due to ECG inherent robustness to circumvention, obfuscation and replay attacks. In this paper, the ECG WATCH, a non-expensive wristwatch for recording ECGs anytime, anywhere, in just 10 seconds, is proposed for user authentication. The ECG WATCH acquisitions have been used to train a shallow neural network, which has reached a 99% classification accuracy and 100% intruder recognition rate.

Keywords: Biometrics, CCA, ECG, EKG, ECG WATCH, Electrocardiogram, Intruder recognition, Multilayer perceptron, PCA, Supervised learning, Wearable device.

1 Introduction

In the last decades, the increasing amount of information technologies, smartphones and wearables, has led to an exponential growth of the data shared on internet. Information is always travelling around, e.g. over Bluetooth. In such a scenario, each piece of information must be accessible only to its authorized users, aka *access control* [1]. Applications such as surveillance, banking and healthcare deal with sensitive data whose confidentiality and integrity depends on accurate human recognition [2]. In this sense, the crucial mechanism for performing an effective access control is *authentication*, which unequivocally yields user identity.

Biometric-based techniques take advantage of intrinsic human properties, such as physiological and behavioural; the former are related to some characteristic of human body like fingerprints [3] and retinas [4], while the latter one relies on the subject behaviour, e.g. typing rhythm, gait, and voice. Since the authentication method needs to be robust to forgery, not every biological parameter can be employed for biometrics. In this sense, it can be used any physiological and/or behavioural feature that fulfils requirements such as universality, distinctiveness and permanence [5].

ECG biometrics. Because of its inherent robustness to circumvention, obfuscation and replay attacks, a biosignals-based approach has been largely explored during the last decades [6]. The idea is to exploit vital signals typically employed for medical diagnoses - such as electroencephalogram (EEG) [6,7], photoplethysmography [8] and electrocardiogram (ECG) [9,10] - for biometric purposes. In particular, the latter is quite interesting because both the physiological and geometrical differences in each human heart correspond to uniqueness in the ECG morphology [11]. In this sense, ECG exhibits various meaningful properties - such as uniqueness, permanence, and ease of collection [9]- that make ECG a preferable choice over both PPG and EEG; compared with classical biometric techniques, e.g. fingerprints, ECG-based methods can definitely be considered a more reliable and safer way for user authentication [12] because:

- ECG is an internal signal and no traces remain after its acquisition, i.e. it is harder to be sniffed without the user noticing.
- The inherent inter-variability of each recording implies ECG is difficult to be fabricated.
- ECG acquisition is less prone to ambient noise than other methods, such as voice [13,14] or face recognition [15], where ambient noise or lighting conditions can deeply affect the recognition process.
- The ECG signal can be acquired via various conductive materials and simple electronics, which can also be easily embedded in fabric or wearables.

Paper outline. The rest of the paper is organized as follows. Sec. 2 presents the state of the art of ECG-based neural biometric techniques. In Sec. 3 the proposed approach, based on wearable devices, is detailed. Sec. 4 illustrates the experimental ECG dataset, whose manifold and intrinsic dimensionality is analysed in Sec. 5. The chosen shallow neural network for user authentication is described in Sec. 6. Finally, Sec. 7 yields the conclusions.

2 State of the art

ECG based biometrics has proven to be robust to both emotional and mental state variations [16]. With respect to the nature of the considered features ECG-based biometric systems can be clustered into three groups: fiducial, non-fiducial and hybrid.

The former approach is based on the extraction of specific points on the ECG heartbeat, called *fiducials*, and their usage as input features, which may also involve their amplitude, angle, or duration. The fifteen fiducial features based on the R peaks used in [17] yield 82% and 79% heartbeat identification rates using two different ECG sites, neck and chest, respectively. The fiducial amplitude and duration, together with QRS and PR intervals, are exploited in [18]; the method reaches 79% and 85.3% of accuracy w.r.t. different lead configurations.

Non-fiducial methods are based on statistical attributes of the signal, in either the time or frequency domain, rather than specific points on the electrocardiogram curve. Autocorrelation and linear dimension reduction using kernel principal component analysis (kPCA) and SVM [19] is used in [20]. K-nearest neighbourhood classifier and Hadamard transform were exploited in [21]. 1-D convolutional neural networks were used in [22]. The discrete cosine transform and autocorrelation coefficients are employed in [23,24,25].

Finally, both fiducial and non-fiducial features are combined in the latter category [26,27], which, in this sense, is called *hybrid*. For instance, [11] presents a technique where the fiducial features are the positions and amplitudes of the P, Q, R, S and T points, while the non-fiducial attributes are represented by the autocorrelation and discrete cosine transform coefficients.

3 The ECG WATCH biometric system

Data breaches can be prevented by using biometric authentication devices for limiting the access to specific software and sites such as airport security areas or hospital neonatal wards. The identity and access management market is quickly increasing (today is bigger than $4bn), with biometric hardware credentials being a key growth trend [28]; specifically, a rising amount of companies is working for using ECG biometrics in both consumer and enterprise applications, such as smart clothing, access control cards and wrist wearables [12].

In this contest, a perfect tool for ECG biometric authentication is the ECG-WATCH [29,30], shown in Fig. 1. It is wearable and unobtrusive; it records, in only 10 s, a single-lead ECG, which will be shown into a smartphone or desktop app; acquisitions are stored in the smartphone in an open format; data can also be shared to physicians for deeper analysis. The device is as big as an everyday watch; thus, it can be constantly worn at wrist without any discomfort for the user; it is low cost (30 €) and, above all, wireless (no long cables are required). In this sense, the ECG-WATCH has been designed as a full-heart-monitoring too; indeed, the app is provided with an automatic silent atrial fibrillation detecting algorithm [31]. The ECG WATCH uses two dry electrodes (one on top and the other on the back) to measure the user electrical potential difference along one of the three peripheral leads (I, II , III) of the Einthoven's triangle [32]: when it placed between user wrists, it acquires the lead I; when signal is recorded among the left leg and the right arm, the device measures the lead II; finally, if it is used between the left leg and arm, it gathers the lead III.

Fig. 1. The ECG WATCH

In [33] authors have proven device acquisition quality, which has been then exploited for pathology recognition through a neural system [34]. In this work, instead of classifying heart diseases, an artificial neural network [35-42] is used for discriminating among different individuals. Due to the employment of wearable devices and mobile apps, and the need of a fast recognition algorithm, a shallow neural network [43,44,45] analogous to the one proposed in [46] is preferred to deeper models such the 1-D convolutional neural network of [47].

4 The experimental dataset

ECGs have been collected in the Neuronica Lab of Politecnico di Torino on six male volunteers: five healthy subjects and one cardiopathic (*Subject3*). All acquisitions were recorded between wrists at 1 KHz; heartbeats (HBs), whose length has been empirically set to twenty time-instants, have been extracted using autocorrelation and discrete cosine transform (DCT). For each volunteer, the number of acquired ECGs, together with the corresponding total amount of HBs, is detailed in Table 1. The final TS has 2331 rows (the cumulative sum of HBs) and 20 columns (the chosen heartbeat size).

Table 1. Dataset taxonomy

	Age	Sex	No. of ECGs	No. of heartbeats
Subject1	26	M	47	429
Subject2	27	M	22	185
Subject3*	60	M	63	748
Subject4	24	M	56	531
Subject5	27	M	20	190
Subject6	23	M	31	248

**Cardiopathic*

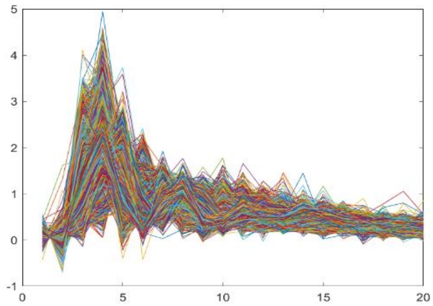
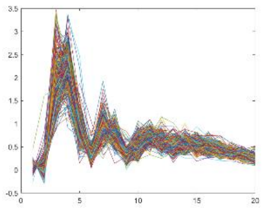
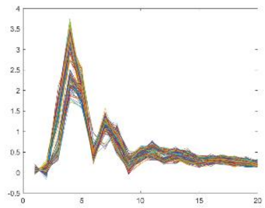


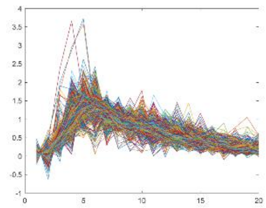
Fig. 2. Heartbeat visualization: whole dataset.



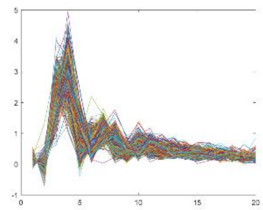
(a) Subject1



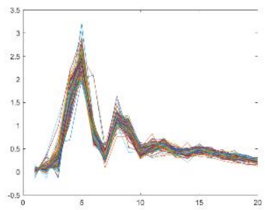
(b) Subject2



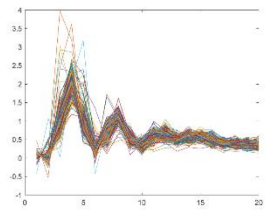
(c) Subject3



(d) Subject4



(e) Subject5



(f) Subject6

Fig. 3. Heartbeat visualization: single subject.

Fig. 2 does not exhibit a common pattern for all the subjects; R-peaks, i.e. the HBs, are somehow distinguishable but the plot is quite noisy. Fig. 3 provides a deeper level of analysis; here, HBs are plotted into a separate subfigure for each subject:

- Subject2 and Subject5 subfigures are very well concentrated around their mean, i.e. the heartbeats are clearly distinguishable.
- Subject6 is thicker around the mean but the overall shape is still appreciable.
- Subject1 and Subject4 are quite noisy.
- Subject3 heartbeats are completely unrecognizable; it can be argued that the morphology loss is due to the cardiovascular disease.

5 Manifold analysis

The database has been studied to determine its intrinsic dimensionality (ID). A preliminary linear analysis has been conducted using the Principal Component Analysis (PCA) [48]. Fig. 4 shows the corresponding Pareto chart [49] computed on the whole dataset, where each column represents the amount of variance explained by the corresponding principal component (of course, the plot has a decreasing trend). Assuming 90% is a significative threshold for the explained variance while ignoring noise, the intrinsic dimensionality can be estimated to 12.

Because of the differences depicted in Fig. 3, each subject samples have been analysed separately; Table 2 summarizes the results: despite the intrinsic dimensionality of the whole dataset is equal to 12, it varies a lot w.r.t each volunteers, from a minimum of 8 up to 15. Interestingly, Subject3, whose plot is the less HB shaped, has also the higher intrinsic dimensionality w.r.t. the PCA linear analysis.

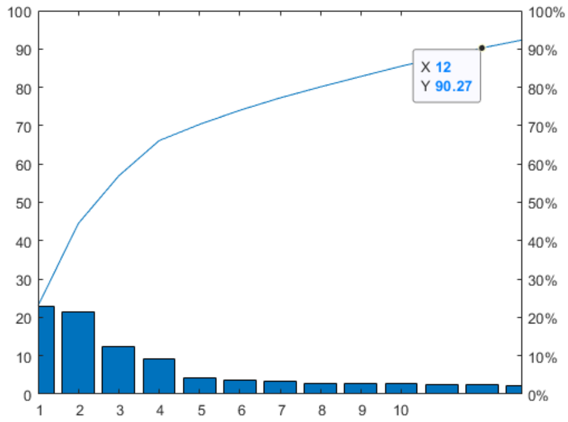


Fig. 4. Pareto chart: whole dataset.

Table 2. Intrinsic dimensionality

	Whole DB	Subject1	Subject2	Subject3	Subject4	Subject5	Subject6
PCA*	12 (90.27)	14 (91.04)	8 (90.12)	15 (92.23)	11 (90.45)	14 (91.44)	13 (91.92)

*in brackets the percentage of explained variance.

6 MLP-based authentication

Although the previous analyses have demonstrated the input dataset is easy to be clustered in terms of healthy and sick subjects, it must be further deepened if it is possible also to recognize each volunteer. The wearable philosophy requires a simple algorithm with regard to both the computational complexity and the time needed for providing a result, i.e. the authorization token; at the same time, the most important constraint to be considered is the accuracy. At this purpose, a simple shallow neural network has been trained. The input layer is mapped one-to-one to the input features; thus, it is made of twenty units. The hidden layer is made of fifty neurons, and the output units are equipped with soft-max activation functions [49]. Due to the cross-entropy error function, the network yields the membership probabilities for each subject of the TS. To balance the overrepresentation (see Table 1) of Subject3 (~ 750 samples), the two youngest attendees (Subject4 and Subject6), were merged into as a single fifth class (~ 780 HBs), say *other*, which is also used for representing *external* people w.r.t. the authentication system. The shallow network has been trained by means of the Scaled Conjugated Gradient algorithm [49]. To preserve the input label distribution, in all the simulations, the input dataset was split into balanced training, validation and test subsets w.r.t the five classes (*Subject1*, *Subject2*, *Subject3*, *Subject5*, *other*). Seventy percent of the TS was used for training, while the rest was divided in equal parts for test and validation sets, respectively.

The training and testing confusion matrices are shown in Fig. 5; in both cases, the overall accuracy exceeds 99%. More in detail, classes 2 and 4 precision and class 3 recall reach 100% for both training and testing, while class 3 precision and class 5 recall are higher in testing than in training.

Class 3 (the cardiopathic attendee) has confirmed to be the simplest to be recognized; however, both the overall and the single class performances are definitely impressive. In this sense, the proposed technique is suitable for the application at hand.

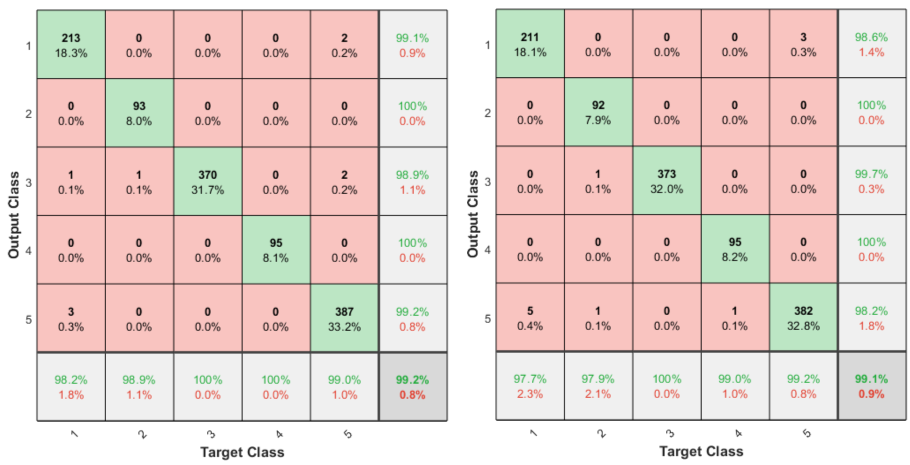


Fig. 5. Shallow neural network confusion matrices: training (left) and testing (right).

6.1 Unknown subject

As a final test, the method robustness has been measured using a novel, additional subject never fed to the network, neither in training nor in test. The scope was simulating a real case scenario, where an intruder tries to deceive the system by means of a fake identity; here, it is modelled using the fifth class, which represent the non-authorized users, i.e. the rejected tokens.

The *intruder* is a ten-years old child, who kindly provided 128 heartbeats. Fig. 6 yields the recall phase confusion matrix: the intruder is never misclassified, which proves the biometric model is robust and can be exploited for real authorization tasks.

Fig. 6. Shallow neural network confusion matrix: intruder simulation

7 Final considerations

ECG-based authentication provides greater security and safety in a world of risk; if used together with other biometrics, it can yield the most powerful digital security strategy; indeed, such an approach may totally modify the security model, from external-based biometric to internal physiological data, which are almost impossible to forge. In this paper, a shallow neural network has demonstrated to be able to recognize subjects and, above all, to detect intrusion attempts. Its robustness has also been proven w.r.t heart pathologies.

Finally, studying vital parameters signals could lead to extrapolate deeper human insights, which could have even more significative applications than authentication. For instance, ongoing researches have explored the usage of wearable devices to assess changes in the human nervous system w.r.t. external inputs [50]: pre-defined emotional states have been related to physiological data acquired with a wristband. In this sense, it can be thought as an advancement towards the understanding of the physiology underlying emotions.

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