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ECGsound for human identification

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ABSTRACT

Novel biometric systems have emerged in recent years as an alternative or complement to traditional identification systems based on passwords (something you know) or tokens (something you have). In this sense, biopotentials signals such as electrocardiograms (cardiac signal) or electroencephalograms (brain signals) have attracted many researchers' attention. This work proposes an innovative identification technique based on electrocardiograms (ECGs) and musical features (e.g., dynamics, rhythm or timbre) commonly used to characterise audio files. In a nutshell, after pre-processing ECG recordings, we transform them into audio wave files, split them into segments, extract features into five musical dimensions and finally fed a classifier with these instances. The proposal's workability is confirmed by experimentation using the MIT-BIH Normal Sinus Rhythm Database with 18 subjects and offering an accuracy of 96.6 and a low error rate with FAR and FRR 0.002 and 0.004, respectively.

1. Introduction

The use of physiological signals has attracted researchers' attention in the last years [1]. Bio-signals have proven to be effective in a wide range of cybersecurity applications, from authentication and identification systems [2–5], through cryptographic primitives [6–9], to key generation algorithms [10–13], to mention few examples. This kind of solutions is universal since vital signals are present in all living people. Besides, the acquisition of long datasets is not very demanding for users, and systems can be updated with a low interference in the daily user life. Regarding performance, the proposed solutions offer high performance, and the systems protect against counterfeiting attacks.

A bio-signal is an electrical and non-electrical signal that can be recorded from biological beings. The electrochemical activity of excitable cells is responsible for bio-potentials (electrical signal). In the body, this kind of cells is in the nervous, muscular and glandular systems. These cells transition from a resting potential to an action potential when stimulated. Biopotential signals such as (electroencephalograms or electrocardiograms) derived from several action potentials produced by a combination of different cells [14,15]. This work focuses on electrocardiograms (ECG) signals since researchers have broadly used them for security purposes in many works [16–19].

The ECG is a graph that represents the changes over the time of the electrical activity of the myocardium (heart muscle). The cardiac muscle alternatively contracts and relaxes. At resting (polarised state), the insides of cells are negatively charged compared to the outsides. The contraction of the myocardium originates the depolarisation. After that, repolarisation occurs when the cells return to the resting state. As a consequence of the depolarisation and repolarisation, we can observe changes in the electrical potential. We can measure these potential changes by placing electrodes on the body.

One cycle of an ECG signal consists of five waves as depicted in Fig. 1. The *P* wave represents the electrical depolarization of the atria. It begins at the sinoatrial node and disperses into both left and right atria. Three waves (i.e., Q, R and S waves) form the QRS complex. It represents the ventricles' depolarisation and requires a higher voltage electrical signal to spread through the ventricle. Lastly, the T wave corresponds to the repolarization of the ventricles [20].

Contribution: Biopotential signals such as the electrocardiogram (ECG), the electroencephalogram (EEG), the electromyogram (EMG) represent the electrical activity of organs and useful for medical diagnosis. In the last years in the literature, we can find many works (handcrafted and non-handcrafted based solutions) which show the feasibility of ECG signals for biometrics identification. In this wave, our

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proof-of-concept proposal is the first contribution to the best of our knowledge, which proposes the use of well-established musical features (e.g., dynamics, rhythm or pitch) to characterise ECG records previously transformed into audio wave files. We have tested a multi-class-classifier (one-against-many identification) and binary-classifier (one-against-all identification). We have employed a public and well-known dataset (MIT-BIH Normal Sinus Rhythm Database) to guarantee our results' reproducibility.

Organisation: The rest of the article is structured as follows. In Section 2, we review the literature related to ECG biometric identification and the existing works focused on detecting cardiac disorders using heart sounds. We introduce the dataset, pre-processing techniques, feature extraction and the two classifiers algorithms used in our experiments in Section 3. In Section 4, we analyse the results for the multi-class and binary classifiers. Finally, we extract some conclusions and compare our proposal with previous works in Section 5.

2. Related work

In this section, we review the most relevant literature related to this work. We start presenting the common approaches followed by authors to design an ECG-based identification system. We categorise the solutions into handcrafted (fiducial and non-fiducial) and non-handcrafted (see Section 2.1 for details). Next, since we transform the ECG records into wave sound files in our proposal, we review the usage of cardio sounds for medical diagnostic and identification purposes (see Section 2.2).

2.1. ECG biometrics: approaches and current trends

In the last years, we can find many works focused on ECG biometric identification [21,3]. We can categorise the existing solution on handcrafted and non-handcrafted features [19]. Likewise, we can classify the handcrafted solutions as fiducial or non-fiducial based methods. The fiducial points of an ECG beat consist of several characteristics points such as the peaks amplitude (Δ_P, Δ_Q, Δ_R, Δ_S, and Δ_T), the amplitude difference between two peaks (e.g., Θ_{PQ} or Θ_{RQ}) or the time interval between two peaks (e.g., Δ_{PQ} or Δ_{RS}). For the delineation of these features, we can employ classical algorithms like the Pan-Tompkins [22], the Hilbert transform [23] or even novel approaches based on deep learning [24]. The existing works commonly use a subset of the features mentioned above to build this kind of identification solutions [25–27].

Non-fiducial based approaches extract the ECG records' statistical features without needing to localise fiducial points [28]. For instance, in [29] or [30], the authors split ECG signal into non-overlapping segments and then computed a normalised autocorrelation for every window. In [31], Sidek et al. propose the use of normalised convoluted signals. In addition to the above, the extraction of features in a transform domain is a broadly used approach [32]. In this wave, in [33], for each ECG segment, the authors extract the DCT coefficients that correspond to the frequency band between 0 and 40 Hz. Wavelet transform, which provides time–frequency representation, is also in an in-depth studied approach [34,10]. The multi-scale time resolutions allow analysing in detail the high-frequency data transitions related to the *QRS* complex and the low-frequency *P* and *T* waves [35].

Lastly, researchers build the vast majority of ECG identification proposals using deep learning [1,3,36]. These non-handcrafted solutions, to a certain extent, avoid the pre-processing and feature-extraction phases and aim to reach better performance and robustness [17]. In [37], Li et al. present a cascade Convolution Neuronal Network (CCN) in which the first CNN is used for feature extraction and the second one for biometric identification. Similarly, in [38] the authors use a deep feature extractor [39] to transform continuous ECG data into a binary code which then used for identification. Luz et al. assess the use of CCN networks for human identification using as possible input the ECG raw signal or the spectrogram image [40]. In [2] Abdeldayem et al., instead of using the spectrogram directly, propose to use spectral correlation images to feed the CNN.

2.2. Cardiac sounds: medical and cybersecurity context

In the medical setting, cardiac sounds have proven as an effective technique to detect cardiac disorders. In the category of handcrafted features, for example, in [41] an ensemble classifier is trained with instances that contain features from time, frequency and time–frequency domains. In [42], Wan et al. use Mel-Frequency Cepstral Coefficients (MFCCs) as features and a classifier based on a Hidden Markov model (HMM) to discriminate between healthy and subjects with murmur characteristics. In the category of handcrafted features, solutions based on deep neural networks have attracted the attention of many

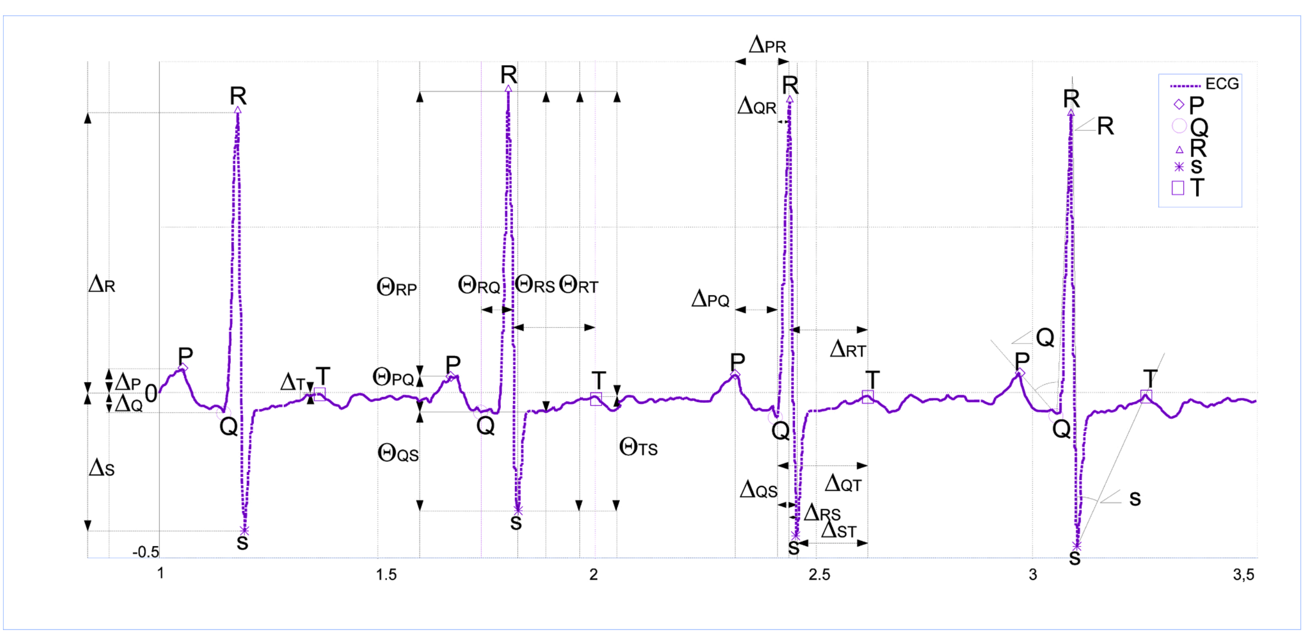


Fig. 1. One cylce of an ECG tracing.

researchers [43,44]. To give some examples, in [45] Bozkurt et al. assess the use of a spectrogram, Mel-frequency cepstral coefficients (MFCCs) or a Mel-Spectrogram as the inputs to a CNN classifier. Similarly, Deng et al. propose improved MFCC features to feed a Convolutional Recurrent Neural Network (CRNN) [46].

Some authors have explored the use of cardiac sounds, specifically phonocardiograms (PCGs), for biometrics purposes in the cybersecurity context [47]. The majority of these proposals extract handcrafted features on a transform domain [48–50]. In this regard, in [51], we can find a comparative study of several cepstral features to characterise PCG records for human recognition. Likewise, Huang et al. propose a multimodal system based on PCG sounds and chest motions to build an authentication system that ensures subjects are alive and prevents impersonation attacks [52]. In 2020, Cheng et al. proposed a biometric solution in which the PCG segments are decomposed into a group of intrinsic mode functions and characterised by dispersion entropy [53].

3. Materials and methods

This section starts by explaining the chosen dataset and how we eliminate noise from each ECG record. After that, we describe how a wide variety of musical features are extracted from each ECG chunk. Finally, we employ a feature selection procedure to reduce the dimensionality problem.

3.1. Dataset and pre-processing

In the literature, we can find a wide variety of ECG datasets [54–56]. The vast majority of those were recorded in a clinical setting, and subjects suffer a cardiac pathology (e.g., arrhythmias or coronary artery disease). In our case (subject identification), a pathology's existence may introduce a bias in the identification process. Motivated for this, we chose the MIT-BIH Normal Sinus Rhythm Database[1] [54], in which cardiologists did not detect significant cardiac conditions in the individuals. It consists of eighteen long-term ECG records of patients treated at Boston's Beth Israel Hospital. Each user sample consists of two leads recordings (ECG1 and ECG2). In our experiments, we use the ECG1 (a modified lead II) Biomd inspired by previous works [57,58]. Regarding the demographic characteristics, the dataset includes five men aged 26 to 45 and thirteen women aged 20 to 50.

Before extracting features from the ECG records, we need to clean the signal [59]. We eliminate the DC component at the first step. After that, we pass the ECG signal through a pass-band filter to eliminate the main noise components (power-line and respiration). We set the lower-cut-off-frequency and the upper-cut- off-frequency to 0.67 Hz and 0.45 Hz, respectively. We follow the above-described procedure with all the records in the database. Once we have cleaned the dataset, we are ready to extract the features. First, we need to convert the ECG records into audio files (i.e., wave files in our experiments[2]). The details of the feature extraction procedure are described below.

3.2. Features extraction

We extract features according to five musical dimensions: dynamics, rhythm, timbre, pitch and tonality [60]. Dynamics in music is about how loud (i.e., from mezzo-forte to fortissimo) or soft (from mezzo piano to pianissimo) the sounds are. The rhythm defines how long or short a sound is. Terms like temp or meters, which refer to the speed and the signature used in the music, respectively, are part of the rhythm feature. The timbre is a specific quality that a particular instrument or voice has. We often use the spectrum and envelope analysis to determine this quality. Pitch classifies sounds depending on their vibration frequency (e.g., 850 Hertz corresponds to a high pitch). Finally, tonality is linked with the idea that musical compositions are organised around a central note.

Feature extraction in audio files is a well-known discipline in contexts such as music or emotion detection [61–64]. We can extract features such as the timbre, pitch or tonality to categorise sound records. This approach with ECG records, to the best of our knowledge, is novel and is inspired by the procedure that doctors and, more particularly, cardiologists follow to diagnose our help status. More precisely and concisely, the cardiologist uses the stethoscope to check our heart's functioning. In this work, we use the sounds produced by the heart for the identification of a subject. We could have used the heart sounds recorded through a stethoscope to acquire the cardiac recordings (i.e., phonocardiograms – PCG). Still, we opted to use electrocardiograms and convert them into audio wave files. The reader should note that PCG and ECG records are related as described in [65] or, more recently, in [66]. We base our reasoning of using the electrocardiograms on three main reasons: 1) the richness of the ECG signal; 2) Authors have used ECG signal extensively for human identification; and 3) the existence of public datasets with long ECG recordings and control users. From the characterisation of these sounds, we employ the features commonly used for musical records.

In our experimentation, we employ the well-known MIRtoolbox to characterise the cardiac sounds [67]. The authors designed this toolbox to investigate the relation between musical features and music-induced emotions. In our work, we aim to use musical features to identify users unequivocally. For each user, inspired by [59], we split the ECG wave file in windows of W seconds. Then, for each window (instance), we extract a vector with N features ($N = 103$ in our experiments).

We use a feature selection algorithm to reduce the dimensionality of the problem to be solved. In detail, we measure the Information Gain (IG) for each attribute concerning the class [68]. Mathematically,

$$IG(Class, Attribute) = H(Class) - H(Class|Attribute). \quad (1)$$

where H represents then entropy. We have computed the IG for each class and then ranked the values from highest to lowest. For the whole dataset, we have repeated the above experiment for a set of windows size ($W = \{5\text{ mins.}, 2\text{ min.}, 30\text{ s.}, 10\text{ s.}, 5\text{ s, and } 5\text{ s.}\}$). In Fig. 2, the thirty-three variables that contribute some information to the identification problem are summarised and displayed in groups (dynamics, rhythm and timbre). The vast majority of features correspond to timbre features (70%), and the resting ones are divided into 24% of rhythm and 6% of dynamics features. All in all, we have a 70% reduction in the dimensionality of the features.

3.3. Classification

This article aims to present a proof-of-concept of using electrocardiograms to build an unmistakable identification system. A classifier is a vital component of the system. There is a wide variety of alternatives for the classifier [69]. We have chosen two well-known supervised classifiers (multilayer perceptrons and random forest) since the purpose of our work is not a comparative analysis of classifiers but to show the feasibility of our approach. In short, we described below the two mentioned classifiers.

3.3.1. Multi-layer peceptrons

Multilayer Perceptrons (MLP) are composed of neurons named perceptrons [70]. A perceptron receives n features as input (i.e., $x = x_1, x_2, \cdots, x_n$), and each of them has an associate weight (i.e. $w = w_1, w_2, \cdots, w_n$). The weighted sum ($u(x)$) of the input features is passed through an activation f function for computing the perceptron's output. Mathematically:

[1] The database is available at https://physionet.org/content/nsrdb/1.0.0/

[2] $audiowrite$('$ECG.wav$',$ECG_{cleaned}$, fs) writes a matrix of cleaned ECG data, $ECG_{cleaned}$, with sample rate fs to a wave file called ECG.wav

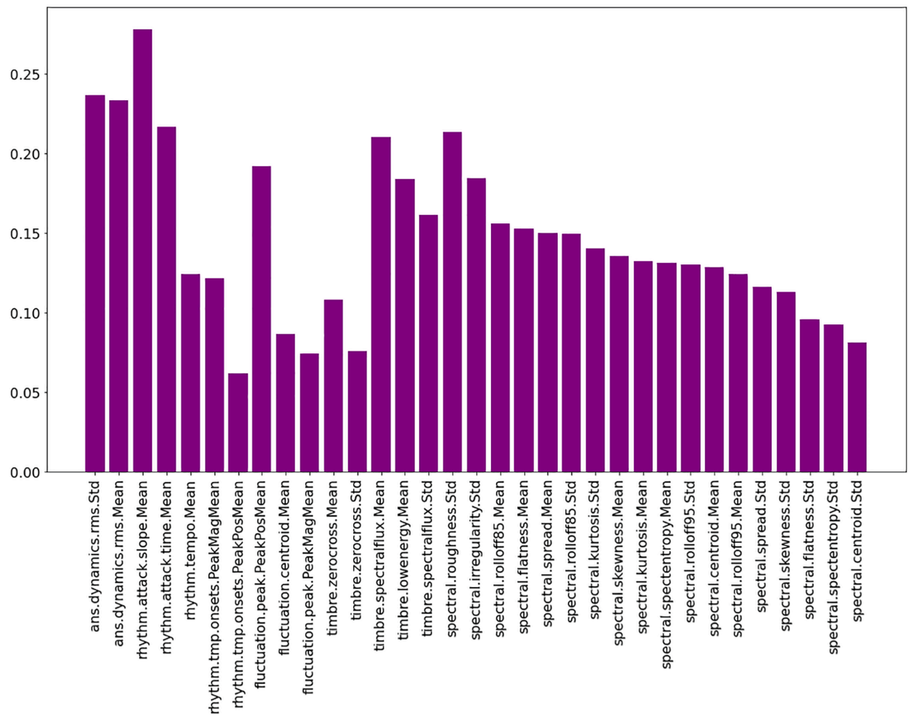


Fig. 2. Features selection.

$$y = f(u(x)) = \sum_{i=1}^{n} w_i x_i \tag{2}$$

An MLP consists of three layers, and we briefly described each of them. The input layer spreads the input features in the first hidden layer. The middle layer is made up of a set of hidden layers of perceptrons. The first hidden layer uses the input features as inputs -the remaining hidden layers employ the previously hidden layer's outputs. Finally, the output layer receives the outcome of each perceptron belonging to the final hidden layer.

The perceptron's weights are adjusted using the training data, aiming to minimise the mean square error. The tuning of parameters is traditionally done using the backpropagation algorithm.

3.3.2. *Random forest*

A decision tree consists of a series of sequential decisions made to reach a particular result. In a Random Forest (RF) classifier, many individual decision trees operate as an ensemble [71,72]. It performs a majority voting (or average value) with each classifier's class outcomes to compute the final output.

The model's fundamental idea is that many relatively uncorrelated models operating together will outperform any individual constituent models. There are two pre-requisites for building effective RF classifiers: 1) the used features have to be representative so that models generated surpasses random guessing, and 2) the predictions, and consequently, the errors of each tree have a low correlation between each other.

In a nutshell, we can summarise the RF algorithm in the following steps:

1. Determine the number of decision trees (N_c).
2. Create N_c datasets (i.e., $D_p, p = \{1, 2, \ldots, N_c\}$), which are called bootstrap samples.
3. Set N_f as the number of features for each split (e.g., square root of the number of features).
4. Determine the impurity measure(e.g., Gini, $I_{Gini}(X_k) = \sum_{j=1}^{p} p(j|k)(1 - p(j|k))$.
5. For each dataset ($p = 1$ to N_c)
   (a) Train the d_p tree employing the dataset D_p and choosing the best split of the N_f randomly-sampled features.
6. Compute the final output via a majority voting with the N_c trees' final outcomes.

Our experiments have tested two scenarios: 1) one-against-many identification and 2) one-against-all identification. For the former, we have assessed the MLP and RF for a set of windows lengths. Since we do not observe significant differences between both classifiers, for the latter, we have only tested an MLP and setting the window length to 30 s. We provide the details of all the conducted experimentation in the following section.

4. Results

Our proof-of-concept aims to answer the two questions about using sound ECG records for identification purposes. First, we design an identification system where the provided template is tested against a set of possible legitimate users (one-to-many comparisons). As a naive example, we might use this solution in a building's access control system where pre-registered users provide a template (a short ECG recording) to enter the facilities. Secondly, we design an identification system with only two classes (the legitimate one and the rests). For instance, we can use this kind of approaches for training the *ID* verification system in our smartphone or smartwatch –modern smartwatches such as Apple watch or Withings Move can easily record with a single lead an accurate ECG trace[3]. Using this approach, we make our system more secure since it learns to distinguish between our samples and others. We make the system resistant against impersonation attacks and implicitly against random guessing attacks [73]. In the two above-described scenarios, we follow the scheme summarised in Fig. 3, and each one of the components has been explained in previous sections.

For assessing the performance, we have used both the typical metrics

[3] https://clinicaltrials.gov/ct2/show/NCT04493749

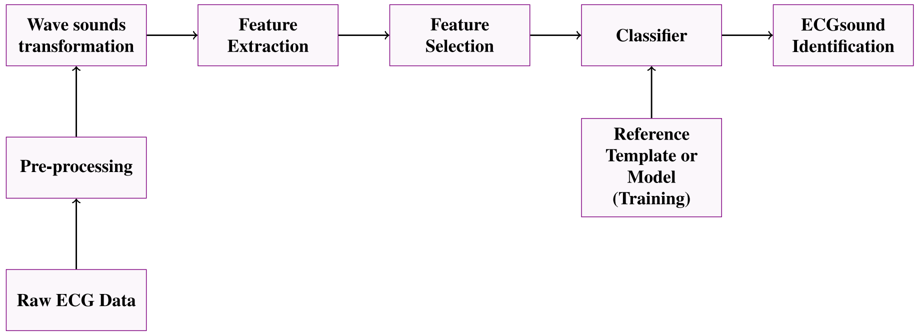


Fig. 3. General structure of a cardiac sound identification system.

used in biometrics and the metrics commonly employed in artificial intelligence. Next, we provide a short definition of this: 1) Accuracy is the number of correct predictions divided by the total number of input samples; 2) F1 score represents the harmonic mean between precision and recall; 3) Precision is the ratio between the number of corrected positive results and the number of positive results predicted by the classifier; 4) Recall is the number of corrected positive results divided by all the instances that the classifier should have identified as positive; 5) AUC (Area under a ROC curve) takes a value between zero and one and is equivalent to the probability that a classifier will rank higher a randomly chosen positive observation than a randomly chosen negative observation. In biometrics, the performance is given using two error rates: False Acceptance Rate (FAR) and False Rejection Rate (FRR). The FAR measures the percentage of unauthorized users classified incorrectly as legitimate users. The FRR represents the portion of valid users wrongly rejected [74].

4.1. One-against-many identification

Using the 18-users of the MIT-BIH Normal Sinus Rhythm dataset, we have designed a multi-class classifier for building the identification system. As mention in Section 3.3, we have tested two classifiers: a Multilayer Perceptron and a Random Forest. Regarding the RF, the depth of three is limited to thirty-three, which is the number of features obtained after the feature selection (see Section 3.2 for details). Concerning the MLP, we set the learning rate, momentum, and the number of epochs to 0.1, 0.2 and 500, respectively.

In Table 1 we summarise the results, using 10-fold cross-validation, for a set of seven performance metrics. MLP classifiers slightly overpass the RF classifiers, but the differences are not very large. A key-decision parameter in the system design is the window size of each instance. We have tested a comprehensive set of possible windows lengths (i.e. $W = \{$ 5 min., 2 min., 30 s., 10 s., 5 s., 3 s. $\}$), inspired by previous works such as [49] or [50]. It is clear from the results that larger window sizes lead to higher performance. Nevertheless, we can not forget the system's usability, and the user will not endure very long periods to determine whether or not she can access the system. Besides, FAR and FRR are critical metrics in biometrics systems. We know that when FAR's value goes down, it implies that FRR's value goes up and vice versa. The point at which both values are equal is named Equal Error Rate (EER). Fig. 4 shows FAR and FRR depending on the window size for the ML (our best classifier). From all these results, as a trade-off between system usability and biometrics performance, we recommend setting the window size in 30 s (or even 2 min, whether supported by the system requirements).

We next review the results obtained when we set the window size to 30 s or 2 min. In Figs. 5a and 5b, we show the normalised confusion matrix. From the above results, we can conclude that the system works properly for the whole set of users belonging to the dataset. None of the users shows abnormal behaviour, and also, there are no gender differences as desirable. The overall accuracy is over 94.5%, which means that users' samples are mostly correctly classified. The good classification performance is also confirmed by the AUC value, which is quite close to one.

Additionally, errors (FAR and FRR) are at a low level using half-minute of window length. The proportion of times a system grants access to an illegitimate user is tiny ($FAR = 0.3\%$). Besides, the ratio of times a system rejects a legitimate user is low ($FRR \leqslant 5.4\%$). In our system, the FAR (rejection of authorised users) is higher than the FRR (unauthorised access). We can compute a parameter K to determine the relation between FAR and FRR (i.e. $K \times FAR = FRR$). For our design, the K is equal to 18 (W = 30 s.) and 17 (W = 2 min.), respectively. The above result is a desirable property in security identification systems since unauthorised access is more dangerous than whether legitimate users are locked out.

4.2. One-against-all Identification

As a supplement to the multi-class classifier, we have analysed the system workability for binary classification. Under this setting, the samples belong to two classes: authorised and unauthorised users. We have designed MLP classifiers for each of the MIT-BIH Normal Sinus Rhythm dataset subjects (i.e., in total, eighteen classifiers; $N_c = 18$). Concerning the MLP parameters, we fixed the learning rate, momentum, and the number of epochs to 0.1, 0.2 and 500, respectively. Besides, we have kept balanced the number of samples of the two classes. Assuming a *subject-p* and acquiring M instances for this target user, we randomly take $M/(N_c - 1)$ samples for each of the resting *subjects-q* (i.e. $q \in \{1, 2, \cdots, 18\} \wedge q \neq p$). In our experiments, each of the subjects has samples from 20 h of ECG recordings ($M = 2400$ samples for windows length of 30 s), and we have tested the system using 10-fold cross-validation.

Table 2 summarises each classifier's results, and all of them offer similar performance (the variance is less than 1.4 for the accuracy and less than 0.015 for the resting metrics). The low variability means that the system is very stable and that the subjects behave the same without any bias and regardless of gender. In comparison to the multi-class-classifier, the accuracy on-average is slightly superior with an increment of 0.5%. Regarding errors, the system works in the EER point with a percentage of errors less than 5% (i.e. $FRR = FAR = 0.0497$). All these above results confirm the feasibility of the one-against-all identification system.

In addition to the above experiments, we have taken into consideration the impersonation attacks. In this kind of attacks, an adversary attempts to bypass the system (e.g., unblock a smartwatch) using signals from subjects non-authorised. Mathematically, assuming a target *user-p* that belongs to the *class-p* and an ECG^q sample of a *user-q* with $q \neq p$:

$$p(\mathscr{A}_I) = p(y = class - p | x = ECG^q) < \alpha \tag{3}$$

We have computed the adversary advantage for impersonation attack against each one of the subjects (classifiers). More precisely, in the testing, we use samples never seen for the classifier and from different users than the target user. From this experimentation, we conclude that,

Table 1
One-against-many Identification for a set of windows length.

Experiment	Accuracy	FRR	FAR	Precision	Recall	F1 Score	AUC
MLP (W = 5 min)	96.6%	0.004	0.002	0.966	0.966	0.965	0.992
Random Forest (W = 5 min)	96.1%	0.039	0.002	0.961	0.961	0.961	0.998
MLP (W = 2 min)	96.6%	0.034	0.002	0.966	0.966	0.966	0.997
Random Forest (W = 2 min)	96.0%	0.040	0.002	0.960	0.960	0.960	0.999
MLP (W = 30 s)	94.6%	0.054	0.003	0.946	0.946	0.946	0.995
Random Forest (W = 30 s)	94.5%	0.055	0.003	0.945	0.945	0.945	0.998
MLP (W = 10 s)	92.0%	0.080	0.005	0.920	0.920	0.920	0.995
Random Forest (W = 10 s)	89.7%	0.103	0.006	0.898	0.897	0.897	0.994
MLP (W = 5 s)	88.5%	0.115	0.007	0.885	0.885	0.885	0.990
Random Forest (W = 5 secons)	85.2%	0.148	0.009	0.852	0.852	0.850	0.990
MLP (W = 3 s)	84.5%	0.155	0.009	0.846	0.845	0.846	0.985
Random Forest (W = 3 s)	81.3%	0.187	0.011	0.813	0.813	0.811	0.986

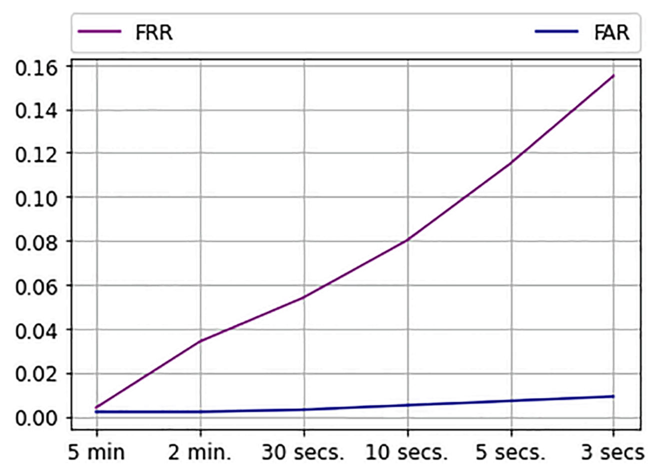


Fig. 4. Determining the window size (W): FRR vs FAR.

on average, the adversary success probability for an impersonation attack is 0.068, which is comparable to the achieved in [52]. This value is small and enough for systems such as the block system of a smartwatch or even a building access control. Likewise, we can also increase this value by assuming a more extended window size (i.e., W parameter in our experiments). Finally, we want to highlight that the resistance to circumvention (i.e., a low probability of impersonation attacks) is vital for biometrics. Our system complies with this property, and this result confirms that the musical features extracted from an ECG record transformed into a wave sound are characteristics of each individual. For the extraction of the features, we use the entire ECG record's richness. Note that an ECG signal comprises several waves (e.g., P, Q, R and S waves). We transform an entire ECG trace into a wave sound preserving all its fruitful.

5. Discussion and conclusions

The resistance to circumvention mentioned above is one of the properties commonly required for a biometric system. The performance, explained in Section 4, is another essential feature for biometrics. We have shown how our proposal offers high achievement in terms of accuracy, *FRR* or *FAR*. Before providing a comparison with other works, we will review the remaining five properties (universality, uniqueness, permanence, collectability and acceptability) that commonly requires a workable biometric system.

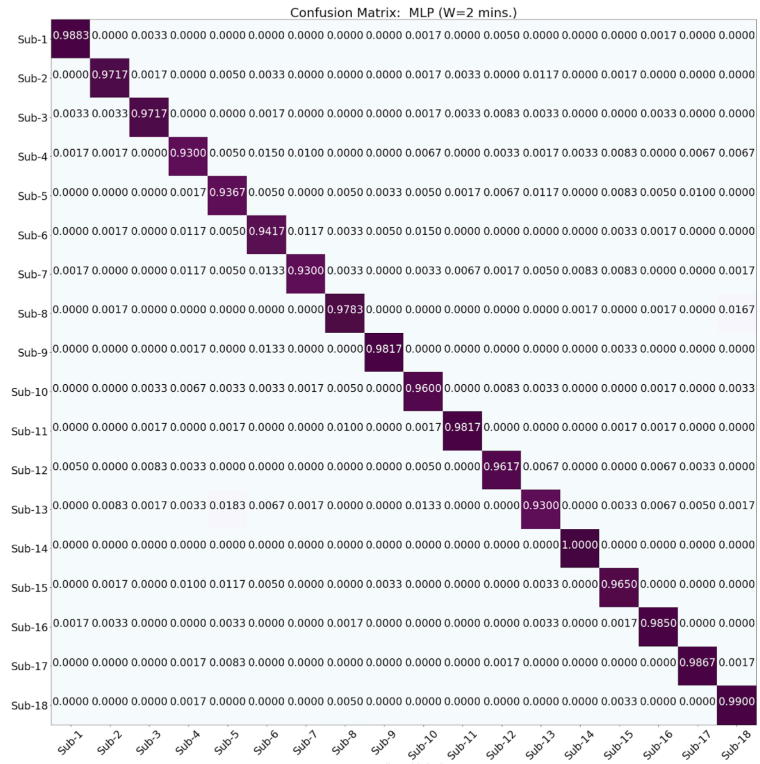
The proposed solution makes use of features extracted from cardiac signals. Universality is guaranteed since everyone alive has a beating heart, and we can record their electrocardiogram. Besides, the signal is available for its recording at any time. Concerning uniqueness, we can find many works based on fiducial and non-fiducial features that show ECG records' feasibility for biometrics purposes [19]. To be the best of our knowledge, this is the first work that shows how we can unequivocally identify users using musical features from an ECG record –the high accuracy and the tiny FAR and FRR are clear indications of a meagre misclassification percentage.

As humans age, our heart signal changes slightly over the years, and we might consider that ECG records are not valid for biometrics due to their permanence. Likely, and despite not being fully invariant over time, cardiac signals are stable during at least five years [59], and after that period, we need to update our system (train the classifier with new user instances). Therefore, workability is assured, and the system is much less demanding in updating those standard password-based solutions that we use in our daily lives [75,76].

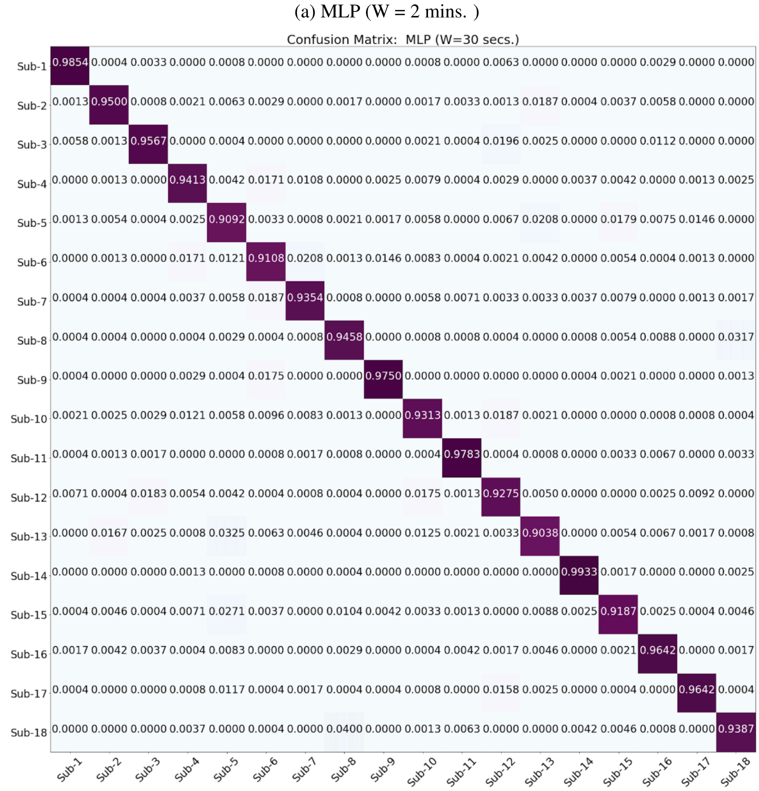
Cardiologists often use an electrocardiogram in their diagnostic tasks. In the medical setting, 12 or 9-lead electrodes systems are used for acquiring the ECG records. Fortunately, in the last years, we can gather reliable ECG records using low-cost hardware (e.g., Bitalino [77]) or even a modern smartwatch (e.g., Apple watch [78,79] or Withings Move ECG [80]) whose ECG traces are medical validated [4]. Therefore there are no doubts about the collectability of our proposal. Concerning acceptability, we can not measure this property directly since we use a known and public dataset in our experiments to ensure its reproducibility. Nevertheless, the possibility of acquiring an ECG through non-invasive devices such as a smartwatch in our wrist (touching it with the hand opposite during a short period) suggests high acceptability. Smart or sport watches are already widespread and widely accepted in the population [81].

Before comparing our proposals with existing works, we highlight that our proof-of-concept aims to bring to the table whether musical features extracted from an ECG record (previously converted into a wave file) are practicable for human identification. We do not intend to make a fully exhaustive comparison but rather compare our solution with the resembling works – the reader is urged to consult [17] for extensive comparatives. In terms of workability and usability, we set the window size to a half minute. In Table 3 we summarize the comparative analysis. We have chosen five handcrafted solutions (three fiducial and two non-fiducial proposals) and three non-handcrafted solutions based on deep learning for comparison. In 2016, Choi et al. [26] proposed an ECG authentication system based on eight fiducial points. The authors tested nine classifiers, including the two ones assessed in this article. Our results and theirs are almost identical in accuracy and AUC but slightly lower in errors (*FRR* and *FAR*). Sidek et al. also tested a multilayer perceptron achieving higher performance than our proposal regarding the accuracy, but no results are provided for errors. In [82] Liu et al. used multiscale feature extraction, and their results are mildly inferior in accuracy and similar in terms of errors. Pinto et al. proposed a non-fiducial approach utilising two transform domains (Discrete Cosine Transform and Haar Transform) and tested several classifiers, including

[4] https://www.clinicaltrials.gov/ct2/show/results/NCT04493749?view = results



(a) MLP (W = 2 mins.)



(b) MLP (W = 30 secs.)

Fig. 5. Normalized Confusion Matrix: ML Perceptron.

an MLP [33]. Our proposal overpasses their results, and only FRR is slightly higher, but the increment is very tiny. In [83], Pathoumvanh et al. studied the robustness of ECG features to heart rate variability, achieving marginally better accuracy but did not provide error values. Finally, in line with the trend of using Deep Learning, Abdeldayem et al. recently proposed an ECG identification system that uses correlation images and a convolutional neural network [2]. Their accuracy is slightly higher (an increase of 1.06%), and the *FAR* is higher than the *FRR* as in our proposal. In [84], Zhang et al. tested a multiresolution 1-D-convolutional neural network with several databases (including the

Table 2
One-against-all Identification ($W = 30$ seconds).

Experiment	Accuracy	FRR	FAR	Precision	Recall	F1 Score	ROC Area
Subjet-1	96.1%	0.039	0.039	0.963	0.961	0.961	0.965
Subjet-2	95.7%	0.043	0.043	0.958	0.957	0.957	0.964
Subjet-3	94.3%	0.056	0.056	0.944	0.944	0.944	0.970
Subjet-4	92.8%	0.071	0.071	0.929	0.929	0.929	0.966
Subjet-5	96.8%	0.031	0.031	0.970	0.969	0.969	0.967
Subjet-6	93.8%	0.062	0.062	0.939	0.938	0.938	0.964
Subjet-7	95.0%	0.050	0.050	0.952	0.950	0.950	0.963
Subjet-8	95.3%	0.046	0.046	0.954	0.954	0.954	0.971
Subjet-9	98.5%	0.015	0.015	0.985	0.985	0.985	0.999
Subjet-10	95.0%	0.050	0.050	0.952	0.950	0.950	0.965
Subjet-11	95.6 %	0.044	0.044	0.958	0.956	0.956	0.965
Subjet-12	94.3 %	0.057	0.057	0.944	0.943	0.943	0.964
Subjet-13	92.7 %	0.072	0.073	0.928	0.928	0.927	0.961
Subjet-14	93.8 %	0.062	0.063	0.939	0.938	0.937	0.962
Subjet-15	94.9 %	0.050	0.050	0.951	0.950	0.950	0.961
Subjet-16	95.6%	0.044	0.044	0.957	0.956	0.956	0.967
Subjet-17	95.5 %	0.045	0.045	0.957	0.955	0.955	0.965
Subjet-18	94.5 %	0.055	0.055	0.946	0.945	0.945	0.960
Overall	**95.0%**	**0.050**	**0.050**	**0.951**	**0.950**	**0.950**	**0.967**

Table 3
A comparative analysis of ECG-based identification solutions.

Proposal	Approach	Database	Accuracy	FRR	FAR	AUC
Our proposal (W = 30 s.)	MLP (handcrafted; non-fiducial)	Physionet-NSRDB	94.6%	0.054	0.003	0.99
Our proposal (W = 30 s.)	RF (handcrafted; non-fiducial)	Physionet-NSRDB	94.5%	0.055	0.003	0.99
Choi et al. [26]	MLP (handcrafted; fiducial)	Proprietary	93.8%	0.085	0.085	0.98
Sidek et al. [86]	MLP (handcrafted; fiducial)	Physionet-NSRDB	99.1%	–	–	–
Choi et al. [26]	RF (handcrafted; fiducial)	Proprietary	95.7%	0.062	0.062	0.99
Liu et al. [82]	RF (handcrafted; fiducial)	Proprietary	93.1%	0.046	0.010	–
Pinto et al. [33]	MLP (handcrafted; non-fiducial)	Proprietary	92.4%	0.033	0.033	–
Pathoumvanh et al. [83]	ED (handcrafted; non-fiducial)	Proprietary	97.0 %	–	–	–
Abdeldayem et al. [2]	2D-CNN (non-handcrafted; non-fiducial)	CEBSDB, Physionet-NSRDB FANTASIA and others	95.6%	0.001	0.022	–
Zhang et al. [84]	1D-CNN (non-handcrafted; non-fiducial)	CEBSDB, Physionet-NSRDB FANTASIA and others	93.5%	–	–	–
Hammad et al. [85]	CNN VGG-Net (non-handcrafted; non-fiducial)	MWM-HIT, PTB and CYBHi	96.8 %	0.03	0.03	–

MIT-BIH Normal Sinus Rhythm Database as in our study). They offered an average identification rate of 93.5%, but they did not provide errors metrics that are critical in biometrics. In line with the above, in [85] Hammad et al. extracted the features of an ECG record using a CNN network (VGG-Net), and their accuracy and error results are comparable to those of our proposal. Finally, we can compare our proposal with two PCG-based proposals in which the authors study several windows sets –these references are omitted in Table 3 since the designers only provide the accuracy as performance metrics. Setting the window size to a half minute, in terms of correctly classified instances, our proposal overpasses to [49] and is lightly below to [50]. That is, our results are also comparable to PCG biometrics works.

The automatic classification of cardiac sound to detect diseases has been carried out for more than 50 years. The first work used a simple threshold-based method and then machine learning, and subsequently, deep learning-based approaches have emerged strongly [87,46]. Xiao et al. recently propose a solution in this wave, which uses a 1-D convolutional neural network to classify heart sounds in two classes (normal or abnormal) [44]. If we abstract from the problem to be solved, in [44] and our work address the classification of heart sounds. Our solution lightly surpasses the work mentioned above in terms of accuracy (96.6% over 93%). Note that what is relevant is not whether we offer superior accuracy but whether our proposal achieves similar performance values to similar works in other contexts (notably the medical setting).

From all the above, our proof-of-concept proposal is competitive in terms of performance and errors compared to the previous ECG-based identification solutions. It is the first work, to the best of our knowledge, in which ECG records are transformed into sounds (wave files) and characterise with musical features for human identification. The use of non-fiducial features avoids the complexity and errors of solutions based on fiducial points (e.g., R peaks., QT interval). Our proposal is much simpler regarding the used classifier than the newest works based on deep learning approaches. Also, the results are comparable to the most current ones in the medical setting in which phonocardiograms are used to detect ailments (e.g., [45] or [46]) or in the cybersecurity context in which PCGs are used for identification purposes (e.g., [53], or [52]).We use the ECG records as inputs for three reasons: 1) ECG records have been widely studied for identification in cybersecurity solutions, 2) ECG records are much more fruitful in terms of information than PCG files, and 3) There exist many public datasets with long ECG recordings and control users. As future work, we will study the combined use of ECG and PCG recordings.Besides, studying datasets with subjects under different conditions (e.g., resting or exercising) and how these can affect system performance is an exciting research line.

CRediT authorship contribution statement

Carmen Camara: Conceptualization, Methodology, Supervision, Writing - original draft, Writing - review & editing. **Pedro Peris-Lopez:** Methodology, Supervision, Writing - original draft, Writing - review & editing, Validation. **Masoumeh Safkhani:** Validation, Writing - review & editing. **Nasour Bagheri:** Validation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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