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Towards a Continuous Biometric System Based on ECG Signals Acquired on the Steering Wheel

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Abstract: Electrocardiogram signals acquired through a steering wheel could be the key to seamless, highly comfortable, and continuous human recognition in driving settings. This paper focuses on the enhancement of the unprecedented lesser quality of such signals, through the combination of Savitzky-Golay and moving average filters, followed by outlier detection and removal based on normalised cross-correlation and clustering, which was able to render ensemble heartbeats of significantly higher quality. Discrete Cosine Transform (DCT) and Haar transform features were extracted and fed to decision methods based on Support Vector Machines (SVM), k-Nearest Neighbours (kNN), Multilayer Perceptrons (MLP), and Gaussian Mixture Models - Universal Background Models (GMM-UBM) classifiers, for both identification and authentication tasks. Additional techniques of user-tuned authentication and past score weighting were also studied. The method's performance was comparable to some of the best recent state-of-the-art methods (94.9% identification rate (IDR) and 2.66% authentication equal error rate (EER)), despite lesser results with scarce train data (70.9% IDR and 11.8% EER). It was concluded that the method was suitable for biometric recognition with driving electrocardiogram signals, and could, with future developments, be used on a continuous system in seamless and highly noisy settings.

Keywords: authentication; biometrics; continuous; electrocardiogram (ECG); identification; off-the-person; outlier detection; signal denoising

1. Introduction

Biometric recognition is gradually becoming a part of our daily lives, as it replaces common identification and access control systems based on keys, cards, codes, or passwords [1,2]. While these can be lost, copied, or stolen, biometric systems are based on intrinsic traits that are always with the person and ensure the correspondence between the subject's and the credential's identities [2,3].

The electrocardiogram (ECG), resulting from the electrical conduction through the heart needed for its contraction, is one of the most recent traits to be explored for biometric purposes [4,5]. Despite being far from as developed or widespread as face or fingerprint biometrics, the ECG offers unique advantages in terms of universality, uniqueness, permanence, and liveness assurance, that attest its potential for the recognition of individuals [5,6].

The use of the electrocardiogram as a biometric trait was first hypothesised in a 1977 US military report [7]. Despite the noticeably lesser acquisition quality, when compared with current measurement systems, ECG was nevertheless considered by this document as a very promising trait.

Hoekema et al. [8] and van Oosterom et al. [9] strengthened this claim by studying in detail the intersubject variability of the ECG.

Biel et al. [10] and Kyoso et al. [11,12], from 1999 to 2001, were the first researchers working on this field. Biel et al. used features directly output by an ECG medical acquisition device, from Lead I, and performed decisions using Principal Component Analysis (PCA) and Soft Independent Modelling of Class Analogy (SIMCA), obtaining 100% identification rate (IDR) with 20 subjects. Kyoso et al. extracted fiducial latency features from CM5 lead signals, and attained 99.5% and 94.2% IDR (with three and nine subjects, respectively), using Mahalanobis distance and Linear Discriminant Analysis (LDA).

In opposition to medical signals, off-the-person signals are quickly becoming commonplace. This designation refers to ECG signals acquired on the fingers or palms of the subjects, using un-gelled electrodes, for higher acceptability and comfort during acquisition, despite the increasing need to overcome significant quality deterioration [13,14]. Chan et al. [15] were the first researchers to explore these acquisition settings for biometrics, with metallic electrodes at the thumbs, obtaining 89% IDR. Coutinho et al. [16] followed, by acquiring signals from the palms, using a conductive mat next to a computer keyboard, and reaching 99.5% IDR. More recently, an off-the-person collection was developed by a group of researchers from the University of Toronto [17] and was used by Louis et al. [18] for authentication, rendering a 7.89% Equal Error Rate (EER) with 1012 subjects.

ECG, being a continuously available signal, opens possibilities for the development of continuous or real-time recognition systems, which is especially advantageous for security or surveillance purposes. Guennoun et al. [19] were the first to explore such systems, for authentication, using fiducial features and Mahalanobis distance, and made decisions according to the individual matching of 35 consecutive heartbeats, obtaining 0.01% False Rejection Rate (FRR) and 0% False Acceptance Rate (FAR). Matta et al. [20] pioneered continuous identification, assessing identity every five seconds with 75% IDR, using autocorrelation features and LDA.

Other aspects that have been explored in ECG biometrics pertain to the effects of heart rate variability, different leads used, and long-term acquisitions. Pathoumvanh et al. [21] verified that the performance (IDR) of their system, based on continuous wavelet transform features and euclidean distance, decreased from 97% to 80% when using signals acquired after exercise. Ye et al. [22] observed that the performance, using Discrete Wavelet Transform (DWT) and Independent Component Analysis (ICA) features with Radial Basis Function (RBF) Support Vector Machines (SVM), on long-term signals is consistently worse than short-term.

Fang et al. [23] and Zhang et al. [24] have concluded, respectively, that using one lead renders significantly worse results than three leads, and that using limb leads such as I or II decreases the performance relative to the use of chest leads V1 or V2. This proves the additional difficulty placed upon off-the-person signals.

The state-of-the-art verifies a clear predominance of bandpass, highpass, lowpass, and/or notch filters for preprocessing of the signals [5,13,14,18,25–34], with fewer researchers opting for line fitting [35,36], DWT [37–41], or Discrete Cosine Transform (DCT) denoising [42]. Reference point detection has been performed in most research works [18,31,33,36,43] as well as signal segmentation in heartbeats [14,18,44] or fixed-size windows [20,30,45].

In what concerns features used, the most frequently extracted and successful were autocorrelation coefficients [5,25,39,46], Fourier, cosine, or wavelet transforms' coefficients [22,26,28,30,34,47], Ensemble Empirical Mode Decomposition (EEMD) [48], averaged ensemble heartbeats [14,27,31,37,42], and several combinations of fiducial amplitude and time measurements [11,12,20,31,49,50]. Decision has been mainly performed through Nearest Neighbours or thresholding [5,14,28,32,35,36,51], SVM [6,22,27,39], or Artificial Neural Networks [40,50,52].

Despite all the evolutions the field has experienced throughout the last two decades, there is still much to overcome. The initiative described in this paper aims to take a leap forward in off-the-person ECG biometrics in a driving environment, useful for automatic personalisation of settings, supervision of professional drivers in fleets, and modelling of driving patterns for detection of distraction moments and fatigue-related accidents [53,54]. It achieved this by overcoming unprecedented noise and signal loss hurdles, characteristic of signals acquired whilst driving, using electrodes embedded seamlessly in a steering wheel cover. Through this, it also aimed to contribute towards reliable continuous ECG-based biometric recognition, using signals acquired in more comfortable and seamless configurations.

2. Proposed Methodology

The devised method aimed for the development of a biometric system that works using ECG signals to frequently recognise the driver. The signals used were acquired continuously and seamlessly on the steering wheel surface of a car. While, in state-of-the-art research, the contact of the subject with the sensor is guaranteed, the frequent hand movements required by the driving activity caused frequent contact loss and saturation periods. These give the signals unprecedented lesser quality, constituting a challenge for the recognition task (Figure 1).

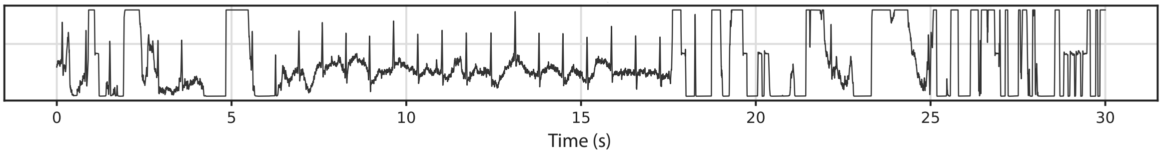

Figure 1. Example excerpt of the signal used, acquired on the steering wheel whilst driving. It is relevant to remark the evident and unprecedented predominance of noise over the signal, especially the effect of varying impedance denoted by the frequent saturation periods, which pose significant threats to the reliability of the recognition process.

After acquisition, the system ensured the relevance of the obtained signal by rejecting samples acquired when the hands were not on the wheel (confirmed by a hardware lead-on detector). Continuous contact periods were partitioned into segments of 5 s and overlap of 4 s, to allow for an initial decision after just five seconds of contact with the wheel, and a renewal of the decision each subsequent second.

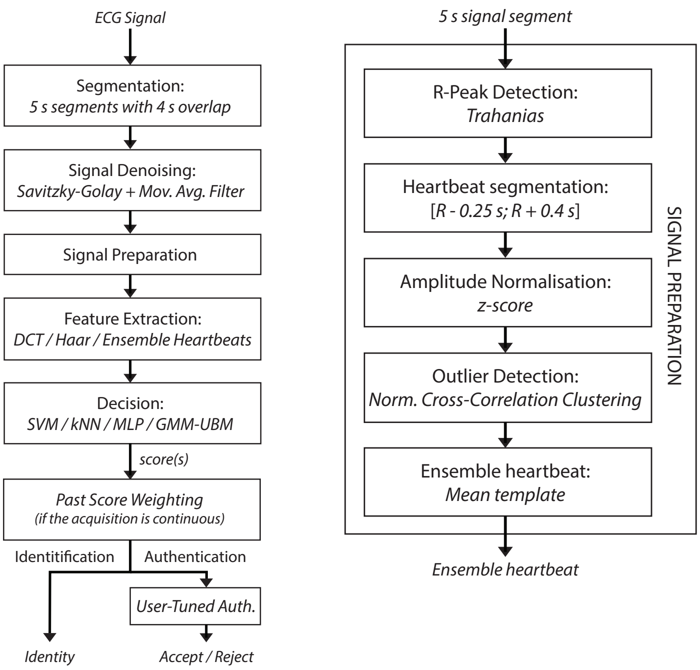

Figure 2. Overview of the proposed method, from acquisition to recognition (**left**), and the detailed process of the signal preparation block (**right**).

The process applied to each five-second frame (Figure 2) is presented in detail over the following subsections.

2.1. Signal Denoising

Common ECG signals used in prior art for biometrics come from either medical acquisitions or, more recently, off-the-person settings. Both of these contaminate the signal with noise, however, it is usually confined to 50/60 Hz (powerline interference) and 0–1 Hz (baseline wander from movement, breathing, and others) [55,56]. Noise in the acquired driving signals is noticeably more dominant and less predictable.

Thus, while methods like bandpass filters [14,18,25,27] or DCT denoising [42] have sufficed in the past, these more adverse signals require methods that make less assumptions on the noise nature and characteristics. The selected approach consisted of a combination of Savitzky-Golay with a moving average filter.

Savitzky-Golay [57] is based on least-squares error minimisation, by fitting a smooth polynomial line among the points in the neighbourhood of a sample and adjusting the latter's amplitude to the fitted line's. This method has excelled, in diverse past applications, in smoothing the signal by removing high frequency noise without causing distortion [35,58]. The moving average filter, based on an implementation through convolution using a 1 s window with overlap, served to complement the action of Savitzky-Golay, by removing low frequency noise, that the latter is unable to clean.

2.2. Signal Preparation

The process of denoising allowed for much cleaner signals. However, distortions like impedance variations and sensor saturation effects (caused by drivers grabbing the wheel with varying tightness), were not adequately removed by the previous phase.

Hence, the signal preparation step (Figure 2) served as intermediate process between denoising and feature extraction, aiming to reject saturation or unacceptably noisy signal segments, which could harm the recognition task.

2.2.1. R-Peak Detection

The fiducial detection required for the segmentation of heartbeats was performed using the algorithm of Trahanias [59]. The algorithm is composed of a filtering phase, which computes the average between the signal after opening followed by closing and the signal after closing followed by opening. Then, a Peak-Valley Extraction (PVE) phase subtracts the signal after opening and closing the filtered signal. This combination of morphological operations enhances the sharpest variations on the signal, which are considered R-peak candidates. Among these, the R-peaks are selected through adaptive thresholding.

2.2.2. Heartbeat Segmentation

The detected R-peaks were then used to obtain heartbeat segments. The segmentation was based on a fixed-window cropping of the signal, 0.25 s before each R-peak and 0.40 s after, as an adaptation of the successful approach proposed by Silva et al. [13]. For all heartbeats analysed during this work, this technique guaranteed the inclusion of all complete waveforms, regardless of heart rate or the duration changes it causes.

2.2.3. Amplitude Normalisation

After segmentation, a normalised version y of each heartbeat segment x is obtained through *z-score* normalisation [30], by subtracting the segment's mean amplitude ($\mu(x)$), and dividing by the standard deviation ($\sigma(x)$):

$$y[n] = \frac{x[n] - \mu(x)}{\sigma(x)} \tag{1}$$

This method provides greater similarity between cleaner heartbeats in all their extension, which benefited greatly the proposed method, especially in the step of the outlier detection. Time normalisation would also be beneficial, due to the varying heart rates while driving. However, it was discarded as it required the localisation of waveform onsets and offsets—highly unreliable in these noisy signals.

2.2.4. Outlier Detection and Removal

For the task of identifying and rejecting outliers among the set of heartbeat candidates retrieved from the five-second segments, a novel approach was devised based on clustering and normalised cross-correlation.

Designated as NCCC (Normalised Cross-Correlation Clustering), the algorithm is centred on the assumption that clean heartbeats of a certain subject, in a short period of time, are very similar between themselves, while false or highly noisy heartbeats are random and different from both clean heartbeats and other false beats.

NCCC consists of the following steps:

1. Compute the normalised cross-correlation between each template (x_i) on the set and each of the others (x_j), with $i, j = 1, ..., N$. From all coefficients obtained, store in NCC_{ij} only the maximum.
2. Get the average normalised cross-correlation for each template:

$$A_i = \frac{1}{N} \sum_{j=1}^{N} NCC_{ij}; \quad (2)$$

3. Arrange A in descending order, and set an initial cluster with the n first templates;
4. Get the mean m of the cluster, and compute $\epsilon = \epsilon_0 * m^2$;
5. Add the next template to the cluster if $m - A_i \leqslant \epsilon \wedge A_i \geqslant 0.5$;
6. Repeat steps 4 and 5 until a template is rejected.

In this specific application, $n = 3$ and $\epsilon_0 = 0.1$ were used. NCCC allowed the selection of only the templates most correlated with the others and, thus, least likely to be an outlier.

2.2.5. Ensemble Construction

The process of signal preparation ends with the construction of an ensemble heartbeat, by averaging the templates selected by NCCC.

2.3. Feature Extraction

Feature extraction aims to capture the individual information present in each ensemble heartbeat, minimising the redundant information, to more efficiently discriminate between individuals. Towards this goal, fiducial and time domain features have been widely chosen on the prior art [29,45,50,60,61].

However, given the variability and noise present in the signals, frequency domain features were selected from the coefficients of DCT and Haar transforms.

- Discrete Cosine transform: The DCT coefficients were extracted from the ensemble heartbeats. The coefficients selected correspond to the frequency range [0, 40] Hz (total of 52 features);
- Haar Wavelet transform: The set of detail coefficients of the second level of decomposition with DWT using Haar wavelets was experimentally selected to serve as feature set for recognition (total of 163 features).

2.4. Recognition

Given a feature vector, recognition models compute and output scores for the claimed identity (for authentication tasks) or for each enrolled identity (for identification tasks). The models explored were:

- Support Vector Machines (SVM): SVM compute an optimal hyperplane dividing two classes, ensuring maximum margin between this boundary and the nearest samples. Kernels can be used to work with non-linearly separable datasets, and multiclass problems can be solved by combining binary classifiers [62];
- k-Nearest-Neighbours (kNN): kNN is a non-parametric, non-linear classifier. Based on the location of the object to be classified, kNN will find the k nearest train samples and predict the class most frequently verified [63];
- Multilayer Perceptrons (MLP): Multilayer Perceptrons are composed by neurons, which apply non-linear operations to their inputs. These are disposed in an input layer, which receives the features; an output layer, which outputs class scores; and a variable number of hidden layers in between. The connections between the neurons have their weights trained through error backpropagation [63];
- Gaussian Mixture Models - Universal Background Models (GMM-UBM): GMM models the distribution of the samples of each individual as a set of normal distributions, whose parameters can be used to classify unknown objects. UBM offers advantages in scarce training situations, by training the model with all samples first, and only then adapting for each subject [64].

Additionally, after the computation of scores by the decision methods mentioned above, in order to enhance the performance of the system by taking advantage of the availability of a claimed identity and the continuous nature of the data, two new techniques were proposed (Figure 2):

- User-tuned authentication: This technique was inspired by the notion of individuality among subjects exposed on Biometric Menagerie [65,66]. As subjects are unique, user-tuned authentication used a bespoke threshold/reference for acceptance/rejection for each enrolled individual, instead of a single threshold shared by all;
- Past score weighting: Outliers are expected to be frequent in highly noisy settings. Past Score weighting aims to reduce outlier influence by adjusting the most recent score using past scores, weighted by their recency. With $p_i(x_t)$ as the probability of the current sample belonging to class i, the weighted score was computed through:

$$p_i^w(x_t) = \frac{1}{\sum_{n=0}^{N} w_{t-n}} \sum_{n=0}^{N} w_{t-n} p_i(x_{t-n}) \tag{3}$$

In Equation (4), N denotes the number of past scores to consider, and score weights w_{t-n} were computed through a half-Gaussian function with tunable parameters:

$$w_{t-n} = e^{-\frac{(t_n - t_0)^2}{2\sigma^2}} \tag{4}$$

3. Results and Discussion

The proposed method was evaluated with excerpts of a continuous ECG recording, acquired over a period of approximately six days. Two excerpts, each with duration of 169–367 s, were randomly selected from two trips of the six drivers and combined in succession to simulate frequent and quick (15–25 s) driver swaps. The two trips of each driver were selected from different days, to maximise the time interval between the excerpts, with the exception of one subject, that only performed one trip.

The signal was acquired with a steering wheel cover, including periods of highway and city driving (higher activity), driver swaps, and idle periods. To the best of our knowledge, no ECG collection in such settings is yet available for use in biometrics research.

3.1. Signal Denoising

The proposed combination of Savitzky-Golay with a moving average filter (SG + MAF) had its performance compared with the most successful prior art methods: bandpass filters (BPF) with bands 1–40 Hz [18,25,26], 2–40 Hz [49,61], 1–30 Hz [27], and 2–30 Hz [16,29]; Savitzky-Golay (SG) [36]; Discrete Cosine Transform (DCT) [42]; and the combinations of Discrete Wavelet Transform with a moving average filter (DWT + MAF) [55] and with a highpass filter (DWT + HPF) [40].

The proposed method excelled with both simulated (clean simulated ECG signals using ECGSYN [67], contaminated with noise expected on driving settings, Figure 3) and real driving signals (Figure 4), by smoothing the signals and avoiding distortion in the best way.

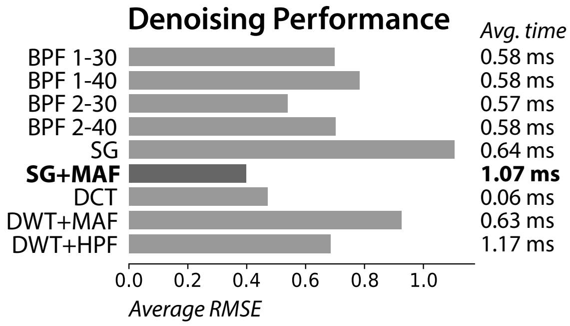

Figure 3. Root mean square error between the clean simulated signals and their versions after contamination with expected noise and denoising with each method. The times required to perform the denoising are also presented.

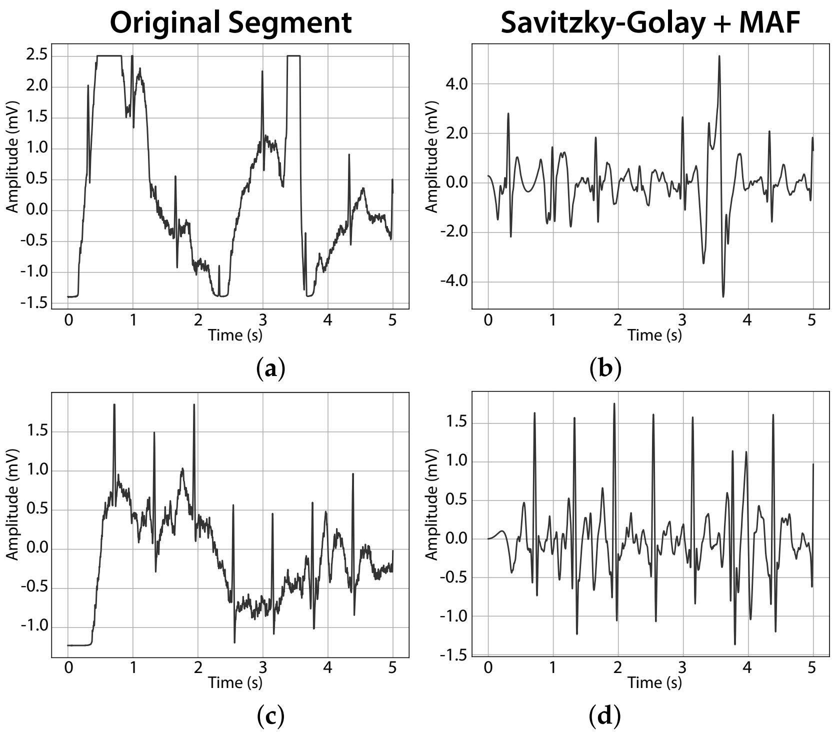

Figure 4. Denoising results in two example five-second segments (the signals were z-score normalised for visualisation; (**a**) first example segment; (**b**) first segment after denoising; (**c**) second example segment; (**d**) second segment after denoising). The proposed combination of Savitzky-Golay and moving average filter was able to adequately clean high frequency noise and baseline wander, despite the persistence of saturation effects.

3.2. Outlier Detection and Removal

The proposed NCCC method was compared with DMEAN [68] in a total of thirty template sets, extracted from segments 5 s to four minutes long, including six to 249 heartbeat templates each

(Figure 5). The results were visually analysed, and the number of templates marked as outliers, the evolution of standard deviation before and after rejection, and the percentage of outliers with initial standard deviation between templates were recorded.

Despite DMEAN's proven effectiveness with cleaner ECG signals, NCCC rejected more noisy and false heartbeats, and more effectively reduced the variance between templates in the set, while keeping most of the cleaner heartbeats. Nevertheless, it was consistently more computationally expensive than DMEAN.

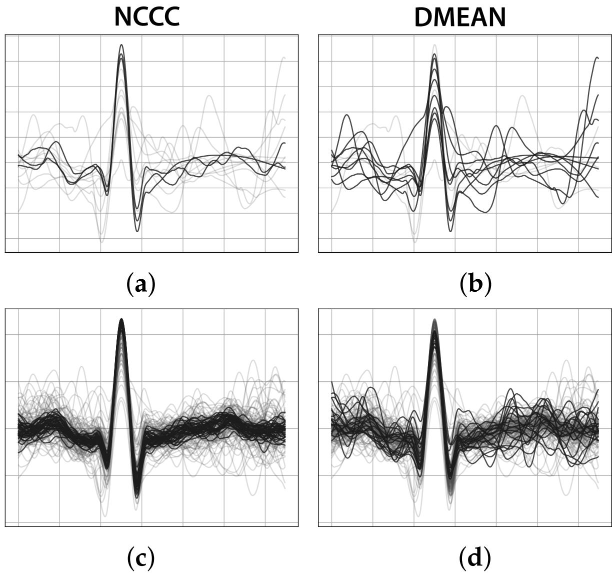

Figure 5. Comparison between DMEAN and NCCC, the proposed approach for outlier detection and removal, with two example template sets (first row: first template set with NCCC (**a**) and DMEAN (**b**); second row: second template set with NCCC (**c**) and DMEAN (**d**); dark lines: Selected heartbeats; light grey lines: Templates rejected as outliers).

3.3. Features and Recognition

The proposed approach was tested for identification and authentication tasks (results presented, respectively, in Figures 6 and 7), in two settings: the first, using 70% of the data of each subject for train and 30% for testing, with cross-validation; and the second, using solely the first 30 s of data of each subject for train.

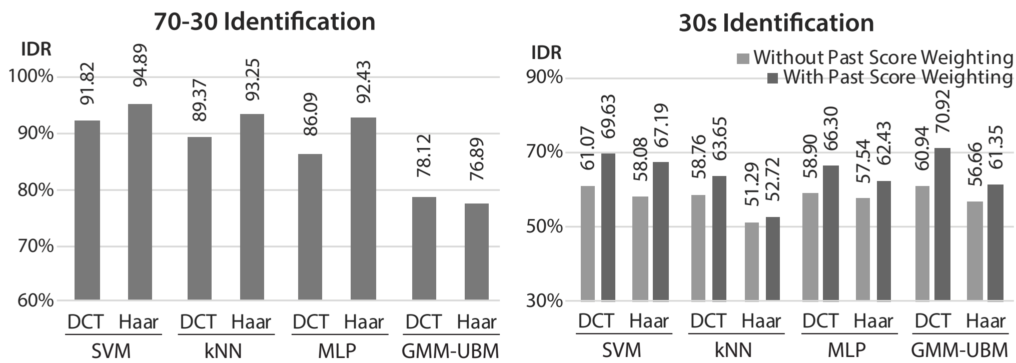

Figure 6. Identification rate (IDR, accuracy) results of the proposed method in identification tasks (left: Results with 70-30 dataset split; right: Results with 30 s train, with and without past score weighting).

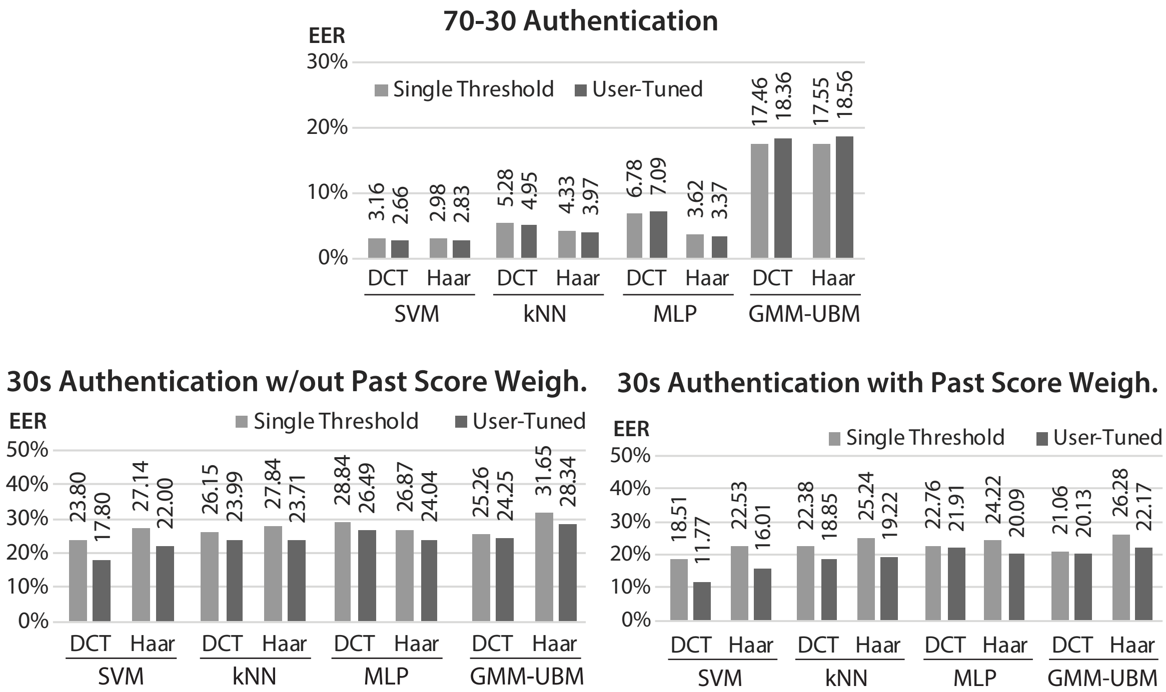

Figure 7. Equal error rate (EER) results of the proposed method in authentication tasks, with and without user-tuned thresholds (top: results with 70-30 dataset split; bottom-left: results with 30 s train; bottom-right: results with 30 s train and past score weighting).

As stated in the proposed methodology, for DCT features, the coefficients that correspond to the frequency range [0, 40] Hz were chosen, as this narrow range contains all useful ECG information. As for Haar features, the detail coefficients of the various levels of decomposition were evaluated in cross-validation identification tasks, individually and combined. The set of coefficients of the second level was found to offer the best combination of better results and reduced dimensionality.

The first setting, 70-30, aimed to allow benchmarking with prior art methods. In both tasks, SVM was the best option, with results similar to some of the best state-of-the-art methods. There was no clear difference between using DCT or Haar features, neither in performance nor in extraction and decision times.

For the scarce data setting, the results were expectedly worse. In authentication, SVM with DCT features remained the best option, but GMM-UBM offered the best result for identification.

User-tuned authentication and Past Score Weighting brought, as shown, significant and consistent improvements in the performance results. It is expected that, with the integration of robust template/model update techniques, these results would experience further improvements.

4. Conclusions

The evident noise predominance over the ECG signals significantly decreased their quality. Nevertheless, the denoising with Savitzky-Golay and a moving average filter and the signal preparation process, that included the formulated Normalised Cross-Correlation Clustering outlier detection algorithm, allowed for the attainment of clean ensemble heartbeats.

These, after feature extraction with Discrete Cosine Transform, and decision with SVM, allowed for the overall best results in both identification and authentication. Moreover, the proposed techniques of User-Tuned Authentication and Past Score Weighting significantly enhanced the method's performance.

Despite the need for further improvements, especially in continuous settings, this paper proves the feasibility of off-the-person ECG biometrics in driving settings. Although there are currently no signal collections available on these conditions, and benchmarking is thus unreliable, the method performed similarly to recent state-of-the-art approaches that used much cleaner signals, generally from medical acquisitions. Thus, the method proved able to recognise individuals using driving ECG signals, and it paved the way towards robust continuous ECG-based biometrics from seamless and highly noisy acquisition settings.

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Author Contributions: A. Lourenço and C. Carreiras were responsible for the development of the acquisition equipment and data acquisition; J.R. Pinto performed the experiments and implemented the proposed method; J.R. Pinto, A. Lourenço, and J.S. Cardoso conceptualised the proposed method, analysed and discussed the results, and drew conclusions; J.S. Cardoso was responsible for the acquisition of funds; J.R. Pinto wrote the paper.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

BPF	Bandpass Filter
DCT	Discrete Cosine Transform
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
EEMD	Ensemble Empirical Mode Decomposition
EER	Equal Error Rate
FAR	False Acceptance Rate
FRR	False Rejection Rate
GMM	Gaussian Mixture Models
HPF	Highpass Filter
IDR	Identification Rate
kNN	k-Nearest Neighbours
LDA	Linear Discriminant Analysis
MAF	Moving Average Filter
MLP	Multilayer Perceptron
NCCC	Normalised Cross-Correlation Clustering
PCA	Principal Component Analysis
RBF	Radial Basis Function
SG	Savitzky-Golay
SIMCA	Soft Independent Modelling of Class Analogy
SVM	Support Vector Machines
UBM	Universal Background Models

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