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# Biometric Authentication Using Noisy Electrocardiograms Acquired by Mobile Sensors

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**ABSTRACT** Electrocardiogram (ECG) signals from mobile sensors are expected to increase the availability of authentication in the emerging wearable device industry. However, mobile sensors provide a relatively lower quality signal than the conventional medical devices. This paper proposes a practical authentication procedure for ECG signals that collected via one-chip-solution mobile sensors. We designed a cascading bandpass filter for noise cancellation and suggest eight fiducial features. For classification-based authentication, we use the radial basis function kernel-based support vector machine showing the best performance among nine classifiers through experimental comparisons. In spite of noisy ECG signals in mobile sensors, we achieved 4.61% of the equal error rate (EER) on a single heartbeat, and 1.87% of EER on 15 s testing time on 175 subjects, which is a reasonable result and supports the usability of low-cost ECGs for biometric authentication.

**INDEX TERMS** Biometric, authentication, electrocardiogram, CardioChip, BMD101.

## I. INTRODUCTION

The rapid growth in physiological sensors, low-power integrated circuits, and wireless communication has enabled body area networks (BANs) [1]–[3]. BANs are now utilized for various purposes such as monitoring traffic, crops, infrastructure, and health [4]–[7]. The progression of BANs is vital, but security remains a challenge yet to be resolved [8]. Biometrics, which is a key solution for security issues, deals with identity-recognition problems by utilizing the biological peculiarity–e.g., voice, retina, fingerprint, blood vessel, face, and cardiovascular cycle. Among them, cardiovascular signals were first proposed by Biel *et al.* [9] as biometric signals measured by electrocardiogram (ECGs). Since the ECG is intrinsically connected to biological functions, circumvention is significantly more difficult than other biometrics such as retina, fingerprint, hand, or face. Measurability and the measuring cost of the ECG is also relatively more reasonable than other biometrics [10].

Starting with the pioneering work of Biel *et. al.* [9], ECG-based biometrics has been steadily studied. The existing methods suggest various approaches to improve authentication performance. An ECG-authentication algorithm typically comprises three steps: preprocessing, feature extraction, and classification [10]. For preprocessing, most algorithms have used bandpass filters [11], [12]; and novel approaches such as wavelet decomposition [13] have also been developed. The feature extraction algorithms can be categorized into two major types: fiducial-based (time domain) [9], [14], [15] and non-fiducial-based methods (frequency domain) [16], [17]. For the classification, various classifiers have been used, such as k-nearest neighbors (kNN) [12], neural networks [18], and support vector machine (SVM) [11].

Most of the methods verified their approach by using open medical data called MIT-BIH and PTB [19], which are available at Physionet (http://www.physionet.org/). The databases offer various types of medical ECGs influenced by heart diseases and conditions, such as sleep stage, apnea, arrhythmia, noise stress, and atrial fibrillation [19], [20]. Various levels of annotations are also available: subject level (demographic information, and diagnostic class), beat level (atrial fibrillation and atrial flutter), and time-point level (peak and end markers for P, QRS, T). Since they are acquired through medical devices, the signals are precise and clean,



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as shown in Fig. 1(a). However, the conventional ECG sensors used in medical devices could not be used for practical applications to mobile biometric authentications due to aspects of high cost and measurability. Recently, real-time health-caring devices are attracting considerable interest, and cardiac-disorder diagnosis techniques are being developed on mobile devices with ECG sensors, such as smart watches, earphones, and smart clothing [21]. The use of low-cost ECG signals from mobile sensors is expected to increase the usability of authentication in actual environments.

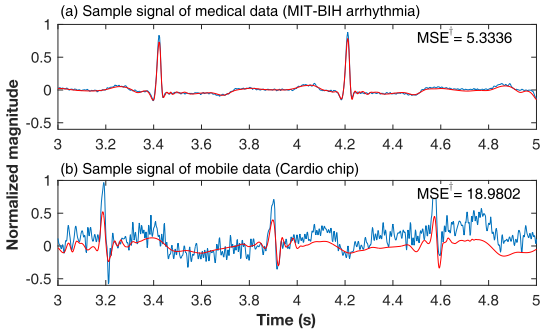


**FIGURE 1.** Comparison of (a) conventional medical data (MIT-BIH [19]) and (b) data from mobile sensor (Cardio chip). Signals of blue line are raw signal of each data, where as those of red line are denoised signal. †MSE refers to mean squared error between raw signal and denoised signal.

In this paper, we propose a practical biometric authentication method using ECG signals acquired via mobile sensors. To acquire ECG signals, we use a one-chip-solution module–i.e., the CardioChip made by Neurosky (http://neurosky.com/), which is shown in Fig. 2. The ECG sensing module is composed of two electrodes, the Bluetooth network module, and an SoC named BMD101. The chip BMD101 provides 0.5-100 Hz signal bandwidth, 512 samples per second (sps) sampling rate, 61 dB SNR, and 3 mm $\times$ 3 mm size.

**FIGURE 2.** Pictures of ECG sensing module named CardioChip (composed of two electrodes, bluetooth network module, and SoC.)

In addition, we validate the actual utility of the present method for biometric authentication via ECG signals acquired by a low-cost mobile sensor. As shown in Fig. 1, the ECG signals from this mobile chip are very noisy, with a high MSE of 18.98, unlike the ECG signals from the high-cost medical device, which has an MSE of 5.33. To remove the various noises embedded in the ECG signals acquired by the mobile sensors, we have designed a band-pass filter by cascading a low-pass filter and a high-pass filter. As the unit of authentication, we present a segmentation from ECG signals into a heartbeat unit, and a feature extraction procedure together with empirically tuned values of parameters. Finally, to achieve a satisfactory performance, a classifier-based authentication scheme is proposed, where training data is constructed to avoid the unbalanced problem in the one-against-all authentication. Nine classifiers are evaluated to choose the best classifier for our authentication purpose.

The rest of the paper is organized as follows: Section II provides preliminary information about ECGs, mobile devices, classifiers, and evaluation metrics. Section III details the methodology specified in four steps. Section IV shows the experimental results. Section V discusses limitations, the difficulty of our approach, and future works. And finally, Section VI provides concluding remarks.

## II. BACKGROUND

### A. ELECTROCARDIOGRAM

Electrocardiogram (ECG) is the physical interpretation of the depolarization electrical activity created by the heart muscles [22]. Propagation of the depolarization as a wave is transmitted to the entire body as well as the heart [22]. This wave produces a current that is individually unique depending on the anatomic structure of the individual heart and body, and the current can be easily detected using skin electrodes. ECG is composed of three main electrical entities that are depicted in Fig. 3: P wave, QRS complex, and T wave. P wave is produced by muscle contraction of the atria. QRS complex marks the ending of atria contraction and the beginning of ventricular contraction. T wave marks the ending of ventricular contraction. The shapes of these entities are determined primarily by human anatomical features so that fiducial information (interval and amplitude) of these entities can be an individually unique feature [23]. In that sense, ECG satisfies the requirements for biometric characteristics [24]: universality (individual possession of

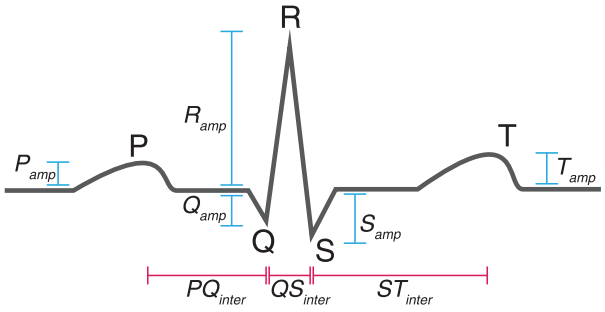


**FIGURE 3.** General ECG signal shape and extracted fiducial feature per beat; $PQ_{inter}$, $QS_{inter}$, and $ST_{inter}$ refers to intervals among peaks. $P_{amp}$, $Q_{amp}$, $R_{amp}$, $S_{amp}$, and $T_{amp}$ refers to amplitudes of peaks.

**TABLE 1.** Mobile health care devices.

| | | | | | |
|---|---|---|---|---|---|
| | | | | | |
| **Category** | Smart watch | Smart watch | Smart watch | Earphone | Sensor |
| **Product** | Galaxy gear S2 | Apple watch | Charge HR | HRM FR74 | iPhone 6/6s Case |
| **Brand** | Samsung elec. | Apple | Fitbit | LG elec. | AliveCor |
| **Release** | Oct. 2015 | Apr. 2015 | July. 2015 | April. 2014 | Jan. 2013 |
| **Price** | $ 300 | $ 400 | $150 | $ 180 | $100 |

the characteristic), measurability (convenience to obtain the characteristic), uniqueness (no identity on two individuals with the characteristics), and permanence (no change in the characteristic over time).

### B. MOBILE DEVICES FOR CARDIOGRAM MONITOR

As mobile technologies have become a powerful form of media for providing individual-level support to health care, plenty of mobile wearable devices have been released by pioneering major companies [25]. Galaxy Gear Fit (Samsung Electronics), Apple watch (Apple), and Charge HR (Fitbit) are the representative products. Not only watches, but also other types of products such as earphones and clothing, have been developed. Table 1 shows the specifications of these representative products, which measure user conditions (exercise quantity, cardiac information, and food-intake patterns) and suggest guidelines for these users. Most key products measure heart rates only, but the devices that provide ECG measurement in addition to the heart rate have also been developed [26]. Even though the current developments for the device with ECG monitoring are only for health diagnosis, this kind of effort will increase the utility of the device with ECG monitoring by easily extending its application to the authentication.

### C. CLASSIFICATION ALGORITHMS

To choose a suitable classifier for our ECG-based authentication, the nine classifiers listed in Table 2 were implemented and evaluated. The classifiers can be categorized into three types: classical, graphical, and ensemble model. Naïve Bayes [27] is a simple classifier that uses conditional independence of each variable and Bayesian properties. Logistic regression [28] measures the linear relationship between the dependent variable and independent variables by estimating probabilities using a cumulative logistic distribution. The support vector machine [29] is a robust classifier with good generalization capability that obtains an optimal hyper-plane that maximizes the margin from support vectors, which is the nearest data from the hyperplane. Bayesian networks [30] are probabilistic graphical models that represent a set of random

**TABLE 2.** Classifier list.

| Type | Classifier name | Reference |
|---|---|---|
| Classical model | Naïve Bayes | [27] |
| | Logistic regression | [28] |
| | Support Vector Machine | [29] |
| Graphical model | Bayesian Network | [30] |
| | Multilayer Perceptron | [31] |
| | RBF Network | [32] |
| Ensemble model | Bagging | [33] |
| | Random Forest | [34] |
| | Adaboost | [35] |

variables and their conditional dependencies via a directed acyclic graph (DAG), which is widely used for hierarchical inference of complex decision systems. Multilayer perceptron (MLP) [32] is a feed-forward artificial neural network with one or more hidden layers, which can work as a universal approximator. MLP is a modification of the standard linear perceptron and can distinguish data that are not linearly separable. The radial basis function (RBF) network [32] is an artificial neural network that uses radial basis functions as activation functions. Bagging [33] trains multiple weak classifiers by bootstrapping, then aggregates the outputs of the weak classifiers to produce a strong classifier. Random forest [34] averages or votes the outputs of multiple decision trees, which is generated by bagging. Adaboost [35] averages the outputs of weak classifiers with weights. Unlike bagging, each weak classifier is trained by the same dataset.

### D. PERFORMANCE EVALUATION METRICS

In this work, we have formulated the problem of authentication as an instance of a binary classification task. Evaluation metrics for the classification performance are based on the notion of true and false positives (TP and FP), and true and false negatives (TN and FN). TP (TN) refers to a positive (negative) instance that is correctly classified as positive (negative). FP (FN) means a negative (positive) instance that is

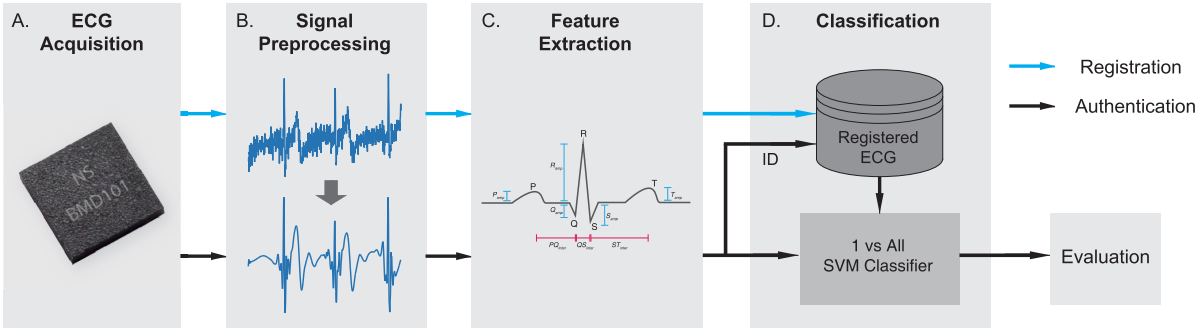


**FIGURE 4.** An overall scheme of proposed framework: (a) acquiring ECG signals via mobile sensor, (b) cancelling noise for robustness, (c) extracting fiducial features in each heartbeat, (d) authenticating an identity through a one-against-all classification. Blue line refers to registration (train) flow and black line refers to authentication (test) flow.

incorrectly classified as positive (negative). Based on classification results, widely used performance metrics have been defined in [36]:

$$\text{Accuracy (ACC)} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

$$\text{Sensitivity (SEN)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{Specificity (SPE)} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{3}$$

$$\text{False Positive Rate (FPR)} = \frac{\text{FP}}{\text{TN} + \text{FP}} \tag{4}$$

$$\text{False Negative Rate (FNR)} = \frac{\text{FN}}{\text{TP} + \text{FN}} \tag{5}$$

Furthermore, area under curve (AUC) and equal error rate (EER) are used to evaluate the performance by varying a discrimination threshold. AUC is the area under the receiver operating characteristic (ROC) curve created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. EER is the error rate at which both FPR and FNR are equal.

## III. METHOD

The overall scheme of the proposed authentication algorithm is depicted in Fig. 4: (a) acquiring ECG signals via mobile sensor, (b) canceling noise for robustness, (c) extracting fiducial features in each heartbeat, and (d) authenticating an identity through a one-against-all classification. More details of each step are provided in the following.

### A. ECG ACQUISITION

For ECG signal acquisition, we used Neurosky's CardioChip, which provides one lead signal by contacting two electrodes with a pair of thumb fingers. Compared to multi-lead medical devices, the device has a higher level of noise. However, the sensor has strong merit in that it can be easily installed to wearable or mobile devices owing to the strength of its small size and its Bluetooth communication module.

In this study, ECG was recorded in a sitting position at a resting state. Each signal is 60 seconds long, with 512 Hz sampling frequency. A total of 175 subjects (144 male and 31 female) participated in our experiments. We acquired the ECG signal once for 78 subjects, twice for 67 subjects, and three times for the remaining 30 subjects.

### B. NOISE CANCELLATION

Noise cancellation should be accompanied, since noise disturbs the robustness of authentication. ECGs commonly contain 60 Hz interference noise, muscle noise ($>$ 40 Hz), and electrode contact noise ($<$ 0.5 Hz) [37]. Since our sensing device has no glue-on electrode, it has much more electrode contact noise than medical devices. Fortunately, the electrode contact noise has a divisibly lower frequency than those of real ECG signals. In addition, the interference noise and muscle noise have a divisibly high frequency. The 5-15 Hz band is appropriate to extract the fiducial feature for authentication [38]. To focus on this band, we adopted a cascading filter that consists of low- and high-pass filters in turn. The transfer functions of the two filters designed are as follows:

$$H_{\text{low}}(z) = \frac{(1 - z^{-6})^2}{(1 - z^{-1})^2} \tag{6}$$

and

$$H_{\text{high}}(z) = \frac{-1 + 32z^{-16} + z^{-32}}{(1 + z^{-1})}. \tag{7}$$

### C. FIDUCIAL FEATURE EXTRACTION

A single ECG has a periodic cycle of three electrical entities (see Fig. 3): a P wave, a QRS complex, and a T wave, generated by atrial depolarization, ventricular repolarization, and ventricular depolarization, respectively [37]. Our algorithm computes an authentication score for each heartbeat, and a procedure is required to segment the whole signal into single heartbeat signals. The segmentation is done by detecting an R-peak in the QRS complex. Based on the detected R-peak location, eight fiducial features ($P_{amp}$, $Q_{amp}$, $R_{amp}$, $S_{amp}$, $T_{amp}$, $PQ_{inter}$, $QS_{inter}$, and $ST_{inter}$) are extracted for each heartbeat as shown in Fig. 3. The detailed procedure to extract the features is described in Algorithm 1. The parameters defining the peak are established by referring to the normal

**Algorithm 1** Fiducial Feature Extractor $\mathscr{F} : \mathbb{R}^l \rightarrow \mathbb{R}^m$

**procedure** Detection of R Peaks
  $R_{candidate} \leftarrow \arg_i(ECG \geq R_{thr} * \max(ECG))$ ▷ Find all the candidate R peaks
  **if** $|R_{candidate}[i] - R_{candidate}[i+1]| < R_{over}$ **then** ▷ Find all the overlap beats which are too close to each other
    $R_{overlap} \leftarrow \arg\max_i(ECG[R_{candiate}[i]], ECG[R_{candiate}[i+1]])$
  $R_{loc} \leftarrow R_{candidate} \setminus R_{overlap}$ ▷ Remove overlap beats from the candidates
  $R_{amp} \leftarrow ECG(R_{loc})$ ▷ Get the amplitude feature of R peaks
**procedure** Detection of Other Peaks
  **for** $i$ to length($R_{loc}$) **do** ▷ Get the location feature of the other peaks which correspond to the $i$th R peak
    $P_{loc} \leftarrow \arg\max_i (ECG[R_{loc}[i] - P_{begin}, R_{loc}[i] - P_{end}])$
    $Q_{loc} \leftarrow \arg\min_i (ECG[R_{loc}[i] - Q_{begin}, R_{loc}[i] - Q_{end}])$
    $S_{loc} \leftarrow \arg\min_i (ECG[R_{loc}[i] + S_{begin}, R_{loc}[i] + S_{end}])$
    $T_{loc} \leftarrow \arg\max_i (ECG[R_{loc}[i] + T_{begin}, R_{loc}[i] + T_{end}])$
**procedure** Computation of Fiducial Features
  **for** $i$ to length($R_{loc}$) **do** ▷ Get the interval and amplitude features which correspond to the $i$th R peak
    $PQ_{inter}[i] \leftarrow Q_{loc}[i] - P_{loc}[i]$
    $QS_{inter}[i] \leftarrow S_{loc}[i] - Q_{loc}[i]$
    $ST_{inter}[i] \leftarrow T_{loc}[i] - S_{loc}[i]$
    $P_{amp}[i] \leftarrow ECG(P_{loc}[i])$
    $Q_{amp}[i] \leftarrow ECG(Q_{loc}[i])$
    $R_{amp}[i] \leftarrow ECG(R_{loc}[i])$
    $S_{amp}[i] \leftarrow ECG(S_{loc}[i])$
    $T_{amp}[i] \leftarrow ECG(T_{loc}[i])$

Parameters:
$R_{thr} = 0.4$ (threshold minimum amplitude of R peak); $R_{over} = 0.1$ s (minimum interval among R peaks);
$P_{begin}$ =$RR_{int}/6$, $Q_{begin}$ =$RR_{int}/10$, $S_{begin} = 0$, $T_{begin}$ =$RR_{int}/10$ (begin points of the peaks);
$P_{end}$ =$RR_{int}/10$, $Q_{end}$=0, $S_{end}$ =$RR_{int}/10$, $T_{end}$ =$RR_{int}/2$ (end points of the peaks).

ECG range suggested in [39]. The values of parameters are described in the bottom part of Algorithm 1.

### D. CLASSIFICATION-BASED AUTHENTICATION

In the authentication stage, the feature vector extracted from each heartbeat is an input to the classifier corresponding to a target user. The classifier produces a score indicating the degree of how much the feature matches the target user. The final authentication is done by the ensemble (arithmetic mean) of the scores from the multiple heartbeats in the window. The larger window size improves the performance but requires more time for authentication. That is, there is a trade-off between performance and authentication time. This trade-off will be examined in Section IV-B.

For the classifier in our work, we have chosen the SVM that has shown the best performance among the nine classifiers presented in Section II-C, through empirical evaluations. For the evaluations, each classification algorithm was implemented by calling the Java object of libSVM [40] for SVM, and Weka [41] for the other algorithms in MATLAB2015a. To evaluate the generalization ability of each classifier, a 10-fold cross-validation has been applied.

For the validation, an early 30-second signal from each ECG is used to train a classifier, and the next 25-second signal is used to test. A set of multiple test signals is established by moving a window every second for an authentication signal.

Let $h_j^{(i)} \in R^l$ and $x_j^{(i)} \in R^m$ be the $l$-length heartbeat ECG vector and the $m$-dimensional feature vector, respectively, of the $j$-th heartbeat of the $i$-th object, where $i = 1, \cdots, M$ and $j = 1, \cdots, N$. Then

$$x_j^{(i)} = \mathscr{F}(h_j^{(i)}) \tag{8}$$

with the feature extracting function $\mathscr{F} : R^l \rightarrow R^m$. To train the one-against-all classifier for the $i$-th object authentication, the positive sample set $\chi_p^{(i)}$ for $i$-th object is constructed by

$$\chi_p^{(i)} = \{x_j^{(i)} | j = 1, \cdots, N\}, \tag{9}$$

whereas its negative sample set $H_n^{(i)}$can be constructed by all samples from the other objects except the $i$-th objects, that is,

$$\chi_n^{(i)} = \{x_j^{(k)} | j = 1, \cdots, N \text{ and } k = 1, \cdots, M \text{ and } k \neq i\}. \tag{10}$$

In this case, the number of negative samples is much larger than that of positive samples, which is known to result in degradation of performance. To balance the two sample sets, we use one representative feature vector per each negative object, by averaging all feature vectors of the object. That is,

$$\bar{\chi}_n^{(i)} = \{\bar{x}^{(k)} | \text{ and } k = 1, \cdots, M \text{ and } k \neq i\} \tag{11}$$

where

$$\bar{x}^{(k)} = \frac{1}{N} \sum_{j=1}^{N} x_j^{(k)}. \tag{12}$$

**TABLE 3.** Classifier comparison results.

| | SVM | Simple Logistic | Naïve Bayes | Random Forest | Adaboost | Bagging | Multi-Layer Perceptron | Bayes Net | RBF Network | Lugovaya *et al.* [23] |
|---|---|---|---|---|---|---|---|---|---|---|
| **ACC(%)** | **95.990** | 93.160 | 90.330 | 95.680 | 94.300 | 94.400 | 93.790 | 94.940 | 93.900 | 96.00 |
| **EER(%)** | **4.460** | 8.810 | 9.510 | 6.230 | 6.510 | 6.720 | 8.540 | 6.100 | 9.300 | - |
| **AUC** | **0.996** | 0.951 | 0.981 | 0.996 | 0.995 | 0.994 | 0.98 | 0.993 | 0.987 | - |
| **SEN** | **0.915** | 0.823 | 0.889 | 0.874 | 0.827 | 0.858 | 0.83 | 0.884 | 0.844 | - |
| **SPE** | **0.972** | 0.964 | 0.908 | 0.981 | 0.977 | 0.969 | 0.97 | 0.969 | 0.967 | - |
| **FPR** | **0.028** | 0.036 | 0.092 | 0.019 | 0.023 | 0.031 | 0.03 | 0.031 | 0.033 | - |
| **FNR** | **0.085** | 0.177 | 0.111 | 0.126 | 0.173 | 0.142 | 0.17 | 0.116 | 0.156 | - |

## IV. RESULTS

Our approach was implemented in MATAB2015a under an Ubuntu 12.04 linux environment. The experiments were carried out on a machine equipped with four AMD 6172 CPUs, 256GB RAM, Radeon 7970 (2048 cores, 3GB) GPU, and a 2TB hard disk.

### A. SINGLE-BEAT AUTHENTICATION PERFORMANCE

To verify the authentication performance of our approach for single beats, testing and training sets were randomly constructed by a 10-fold cross-validation strategy. Table 3 shows the performance of each classifier in terms of six evaluation indices, which have been described in Section II-D. Each classifier's performance was averaged on all 175 subjects. In each type of classifier, SVM [29], Bayesian network [30], and random forest [34] each showed satisfactory performance with an EER of 4.46%, 6.1%, and 6.23%, respectively. The Radial Basis Function (RBF) kernel-based SVM [29] was the best classifier among all the classifiers used. By parameter tweak, the sigma value of the RBF kernel in SVM was set to 1.5, which showed the best performance. As shown in Table 3, the proposed scheme (SVM), even using a noisy signal, achieves a satisfactory performance comparable to the results of Lugovaya's work, which used an ECG signal from the medical device [23].

### B. ACTUAL AUTHENTICATION SCENARIO

Since the RBF kernel-based SVM showed the best performance on a single heartbeat, an actual authentication scenario was verified, with an increasing test time from 3 to 15 seconds. As shown in Fig. 5, the more test time was used, the more accurate a performance was achieved. Compared with the scenario using three seconds of test time, the 15-second scenario shows about 3.91 times higher accuracy in terms of EER. We could achieve a stable authentication performance owing to the ensemble scores of multiple heartbeats.

## V. DISCUSSION

Fig. 6 shows score histogram examples of ECG signals that give a high accuracy or a low accuracy depending on a subject. Fig. 6(a) depicts the score histogram of a high authentication performance signal (0.42% EER). The distribution of both positive and negative objects had complete partition on

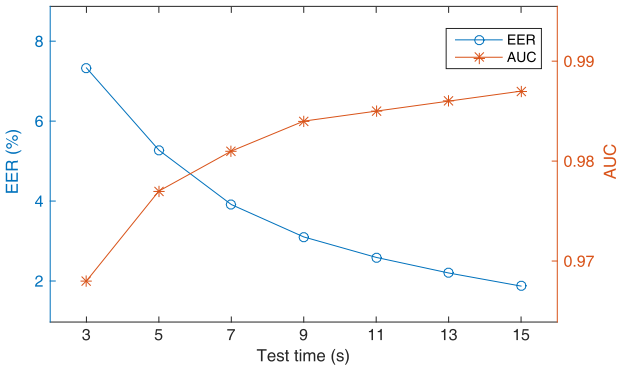


**FIGURE 5.** Test time validation. Performance trends on EER (blue) and AUC (red) as function of extended test time.

threshold 0.7. In contract, as shown in Fig. 6(b), the score histogram of a relatively low-performing signal (19.50% EER) had an overlapping region that yields uncertainty on the classification.

We identified two main reasons by analyzing the low-performing signals. One is the extreme noise that is caused by movement in measuring the ECG signal. The other is the failure of R peak detection in extracting the fiducial feature. For more precise noise cancellation, empirical mode decomposition (EMD) [42], wavelet decomposition [43], or sparse derivative [44] could be used. Non-fiducial features that do not need to detect certain characteristic points could be expected to increase robustness [45]. Although our approach is based on shallow learning, deep learning approaches such as convolutional neural networks (CNN) [46] or recurrent neural networks (RNN) [47] could be used to further improve performance.

Our signals were acquired in a resting state; however, ECGs have characteristics that are influenced by the degree of stress or excitation. When we consider multiple sessions, the performance is usually degraded [45]. Our approach should thus be verified by multi-session ECG signals with various conditions.

One of the difficulties we faced during our study lay in data acquisition. The difficulty was to set some thresholds or hyper-parameters such as the bandpass width at noise cancellation, fiducial peak range at feature extraction, or kernal types and the sigma value for SVM.

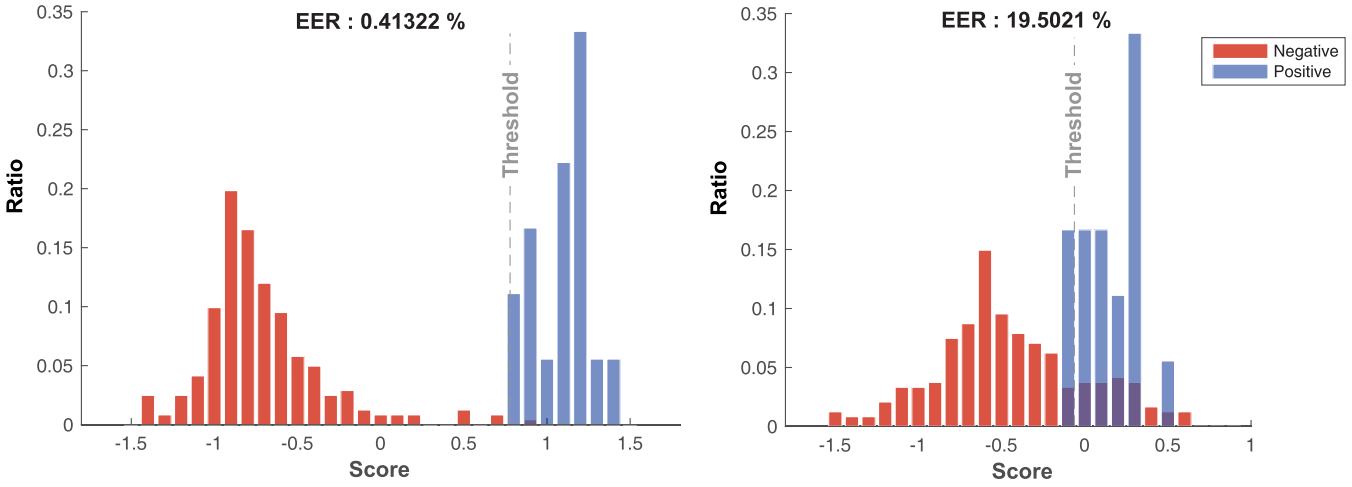


**FIGURE 6.** Investigation on authentication results: score histogram examples of ECG signals that give the low EER (a) or a high EER (b). The red (blue) bar refers to a score histogram of the negative (positive) class. The gray dot line depicts the decision threshold for authentication.

## VI. CONCLUSION

In this paper, we have proposed a mobile sensor-based ECG authentication scheme to be applied to mobile health-care devices, the market of which is expanding. To achieve a satisfactory performance in actual applications, we designed a cascading filter to remove the various noises embedded in the ECG signals acquired by the mobile sensors. In addition, we proposed an authentication scheme containing an ensemble of one-against-all SVM classifiers. To train each classifier, we made balanced training data by using one representative feature vector per each negative object. This approach solves the bias problem typically encountered in the one-against-all classifications. The proposed method showed EER 4.46% for the single heartbeat, and 1.87% for 15 seconds' testing time on the 175 subjects in spite of the sensor's imprecision.

This results are competitive to medical device-based research.

In this respect, the present work makes a contribution to the improvement of the following aspects in the authentication:

- Handy ECG acquisition by using a one-chip-solution mobile device;
- Successful noise cancellation in spite of a low-quality ECG signal;
- Balancing training data that solves the bias problem of one-against-all classifications.

Given these contributions, this research is meaningful in that the results provide the potential applicability of ECG authentication to mobile devices.

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