ECG-based identity recognition via deterministic learning

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ABSTRACT
In this paper, a novel method based on electrocardiogram (ECG) signals is proposed for identity recognition. A unique feature called dynamics, which is fundamentally different from features used in literature, is extracted from ECG signals and used for identity recognition. Deterministic learning, a recently proposed machine learning approach, is used to model the dynamics of training ECG signals. A set of estimators employing the modelling results of training ECG signals is constructed. Through comparing the test ECG signal (measured from a subject to be recognized) with the estimators, a set of errors can be obtained and used to measure the similarity between the test and the training ECG signals. The test ECG signal is recognized in accordance with the smallest error, and then the subject can be recognized rapidly. Experimental results indicate that the proposed method is reliable and efficient for identity recognition.

Introduction
There is growing consensus that identity recognition has potential applications in many areas for security needs. Code lock is one of the most familiar security systems in daily life. However, its security level is very limited, as it can be cracked easily, even though variable password policies (e.g. mixture of lowercases and uppercase letters, periodic scheduled password changes) have been introduced [1]. To achieve a higher security level, more complex security systems have been invented based on human biometric traits (e.g. fingerprint, face, iris) and behavioural characteristics (e.g. gait, keystroke) [2]. However, these traits suffer from either unreliable performance in recognition accuracy (e.g. gait, keystroke) or susceptibility to forgery, such as the progress in the falsification technology (e.g. fingerprints can be easily obtained and replicated by using latex; the face is sensitive to artificial disguise) [3,4].

An electrocardiogram (ECG) is the recording of the heart’s electrical activity, and can be easily measured from the body surface. Its nature is greatly personalized, since it relies on the properties of heart structure and function; thus it can be used as a biometric trait for identity recognition [5,6]. Moreover, comparing with other biometric traits, it has the following properties for identity recognition: (i) it is difficult to forge [6,7] and can only be measured from living individuals [6,7]; (ii) it has a good stability and reproducibility [8,9]; (iii) it contains information pertaining to psychological, physiological and clinical states [6,10], which may be of interest. Extensive studies have been conducted for ECG-based identity recognition since the pioneering works [8,11,12].

The extraction of features that can truly characterize ECG signals is the primary problem in ECG-based identity recognition. The features used in the literature include fiducial features (e.g. QRS duration, T wave amplitude) derived from characteristic points of ECG signals [7,8,10,11], non-fiducial features derived from segmented windows of ECG signals [13,14] and hybrid features [3,15]. However, these static features cannot characterize ECG signals adequately, since ECG signals are essentially temporal patterns (i.e. time-varying patterns) with significant variations [16,17]. Identity recognition based on ECG signals is actually a temporal pattern recognition problem. The existing classifiers developed for static patterns might prove inappropriate for ECG-based identity recognition [18]. It is supposed in [19] that methods for temporal pattern recognition should be fundamentally different from those for static pattern recognition.

As a matter of fact, temporal pattern recognition is one of the most difficult tasks in pattern recognition [20]. Recently, a novel algorithm called deterministic learning theory [18,21,22] was proposed to process the temporal patterns. The dynamics of a temporal pattern can be accurately modelled and represented in a...
time-independent manner by using deterministic learning [19]. Especially, the representation contains complete information of the temporal pattern. Based on the representation, a mechanism to measure the similarity between temporal patterns was proposed in [18,22]. As the dynamics of temporal patterns contain complete information, it is more appropriate to recognize temporal patterns with large variations in morphology (e.g. electrocardiograph, electroencephalograph).

In this paper, we propose a novel method for identity recognition based on ECG signals. The unique feature dynamics is used for ECG-based identity recognition. The dynamics of a training ECG set is first accurately modelled (i.e. extracted) and represented as constant radial basis function (RBF) networks. For a test ECG signal from a subject that needs to be recognized, a set of errors can be obtained by employing the modelling results. The test ECG signal can be recognized rapidly in accordance with the smallest error, and then the subject can be recognized. To test the proposed method, we conducted three experiments on the Physikalisch-Technische Bundesanstalt (PTB) public database [23], which is an ECG collection and is mainly used to evaluate algorithms for ECG processing.

Compared with existing studies on ECG-based identity recognition, the main advantage of the method is that the ECG dynamics containing complete information of the ECG signal is used for identity recognition. The time and frequency-domain features used in existing studies contain only limited information of ECG signals and cannot characterize the ECG signals adequately due to the huge variation in ECG morphology. Particularly, these features are sensitive to various noises, which will influence the recognition accuracy seriously on a large database. Second, the ECG signal is a kind of temporal pattern. The recognition methods for static patterns may be inappropriate for ECG recognition. We present a novel recognition approach based on dynamics. In addition, the recognition process does not need to extract any feature from the test ECG signal and begins with measurement of the state of the test ECG signal; thus the recognition can be achieved rapidly.

**Materials and methods**

**ECG recordings**

In this paper, we collected ECG recordings from the Physikalisch-Technische Bundesanstalt (PTB) diagnostic ECG database to test the proposed methods. The database contains 549 recordings from 290 subjects, including healthy subjects and patients with different heart diseases. Each ECG recording consists of standard 12-lead ECG signals and three Frank leads ECG signals [24]. To test the proposed method for identity recognition, we needed at least two ECG recordings for each subject: one was used as a training pattern and another one was used as a test pattern. Thus, a subset consisting of 14 healthy subjects and 99 patients selected from the PTB database, who have at least two ECG recordings (details can be seen in Table 1), were used to test the identity recognition method. In addition, the average time interval between any two ECG recordings of the same subjects was about 500 days.

**Deterministic learning theory**

Deterministic learning theory [21] has been explored for modelling, representation, similarity definition and rapid recognition of temporal patterns. This theory is essentially based on concepts and theories of system identification, adaptive control and RBF networks. By the deterministic learning algorithm, the dynamics of a temporal pattern can be accurately modelled, and the temporal features of the pattern can be effectively extracted and represented in a way that is invariant in time [19,18,22]. In deterministic learning, a temporal or dynamical pattern is defined as the periodic or recurrent (quasi-periodic, almost periodic and even chaotic signals (or trajectories) generated from the following general nonlinear dynamical system:

\[
\dot{x} = F(x; p), \quad x(t_0) = x_0
\]

where \(x = [x_1, \ldots, x_n]^T \in \mathbb{R}^n\) is the system state, \(F(x; p) = [f_1(x; p), \ldots, f_n(x; p)]^T\) is an unknown continuous nonlinear function vector, the system dynamics, and \(p\) is a constant parameter vector. The system trajectory starting from \(x_0\) is denoted as \(\phi_\cdot(x, t; x_0)\) or \(\phi_\cdot\) for conciseness of presentation. It is assumed that \(\phi_\cdot\) is in either a periodic or a recurrent motion (i.e., a temporal pattern).

To achieve modelling of the unknown system dynamics \(F(x; p)\) underlying the dynamical pattern \(\phi_\cdot\), the following estimator system using the RBF network is employed:

\[
\dot{x}_i = -a_i(x_i - x_i) + \tilde{W}TS_i(x)
\]

where \(\dot{x}_i\) is the estimator state; \(x_i\) is the system state of (1); \(a_i > 0\) is a design parameter; \(\tilde{W}TS_i(x)\) is RBF networks; and to approximate the dynamics

| Diagnosis result | Healthy | Patients |
|------------------|---------|----------|
| Number of recordings | 2 3 5 7 2 3 4 5 | |
| Number of subjects | 7 5 1 1 20 29 48 2 | |
The cal conductivity of myocardial cells, torso and body ingredients, such as heart structure and function, electrical system generating an ECG signal, since it involves many dimensional continuous nonlinear dynamical system. Learning. The ECG signal is generated by the heart electrical activity. Based on this fact that the ECG signal is quasi-periodic in time, it is a kind of temporal pattern in the sense of the temporal pattern definition proposed in deterministic learning. The ECG signal is generated by the heart electrical activities, which can be seen as a complex, high dimensional continuous nonlinear dynamical system. However, it is impossible to derive an exact dynamical system generating an ECG signal, since it involves many ingredients, such as heart structure and function, electrical conductivity of myocardial cells, torso and body fluid.

\[ f_i(x; p) \] of (1), with \( \dot{W}_i = [W_{i1}, \ldots, W_{iN}]^T \in R^N \) and \( S_i(x) = [s_{i1}(|x - \xi_1|), \ldots, s_{iN}(|x - \xi_N|)]^T \), \( F(x; p) = [f_1(x; p), \ldots, f_n(x; p)]^T \), \( s_j(\cdot) \) being Gaussian function, \( \xi_j(j = 1, \ldots, N) \) are distinct centres.

Subtracting system (1) from system (2), we have

\[ \dot{x}_i = -a_i x_i + W_i^T S_i(x) - f_i(x; p) \] (3)

where \( \dot{x}_i = \dot{x}_i - x_i \) is the state estimation error. Based on the universal approximation of RBF networks, there exists an ideal constant weight \( W_i^* \) so that \( f_i(x; p) \) can be approximated as follows:

\[ f_i(x; p) = W_i^T S_i(x) + e_i \] (4)

where \( e_i \) is the approximation error which can be made arbitrarily small. If we denote \( W_i = W_i - W_i^* \), then Equation (3) can be rewritten as follows:

\[ \dot{x}_i = -a_i \dot{x}_i + W_i^T S_i(x) - e_i \] (5)

The weight estimates \( \dot{W}_i \) are updated by the following law:

\[ \dot{W}_i = \dot{W}_i - \Gamma S_i(x)x_i - \sigma_i \Gamma_i \dot{W}_i \] (6)

where \( \Gamma_i = \Gamma_i^T > 0, \sigma_i > 0 \) is a small constant.

It has been shown in [18,21,22] that for almost every temporal pattern \( \phi_t \), the unknown dynamics \( f_i(x; p) \) can be accurately modelled along the trajectory \( \phi_t \):

\[ f_i(\phi_t; p) = W_i^T S_i(\phi_t) + e_{\phi t} = W_i^T S_i(\phi_t) + e_{\phi t} \] (7)

where \( W_t = \text{mean}_{\epsilon \in [t_a, t_b]} W\epsilon(t) \), \( 0 < t_a < t_b \) represents a piece of time segment after the transient process and \( e_{\phi t} = O(e_{\phi t}) = O(e_{t}) \) is the practical approximation error. This implies that the dynamics \( f_i(\phi_t; p) \) underlying almost every dynamical pattern \( \phi_t \) can be accurately modelled via deterministic learning.

**Methods**

Based on the fact that the ECG signal is quasi-periodic in time, it is a kind of temporal pattern in the sense of the temporal pattern definition proposed in deterministic learning. The ECG signal is generated by the heart electrical activities, which can be seen as a complex, high dimensional continuous nonlinear dynamical system. However, it is impossible to derive an exact dynamical system generating an ECG signal, since it involves many ingredients, such as heart structure and function, electrical conductivity of myocardial cells, torso and body fluid.

Let us assume the dynamical system is represented as follows:

\[ E(t) = G(E(t)) \] (8)

where \( E(t) = [e_1(t), \ldots, e_N(t)]^T \) is the ECG signal, \( G(E(t)) = [g_1(e(t)), \ldots, g_N(e(t))]^T \) is the system dynamics that generate the ECG signal \( E(t) \), an unknown nonlinear function vector. Thus, if the system dynamics \( G(E(t)) \) can be accurately modelled and used for identity recognition, it will be more reliable and suitable than static features used in literature.

**Remark 1.** In clinical practice, there are different lead systems for measuring ECG signals, including the standard 12-lead ECG, vectorcardiogram, body surface potential mapping and signal-averaged ECG. In the system (8), \( N \) is the number of leads. In this paper, 12-lead ECG signals will be used for identity recognition, since this is the most common lead system of monitoring a person’s cardiac activity [25] and is widely used in clinical practice. Moreover, the 12-lead ECG signals have been shown to be more suitable for identity recognition [26].

In this paper, we propose a novel method for ECG-based identity recognition based on the 12-lead ECG signals. The method consists of two phases: a training phase and a recognition phase (due to the limitation of space and the purpose of the paper, removing the noise from the ECG signal is not stated here, since it has been extensively studied). In the training phase, the dynamics of the training ECG signals will be accurately modelled by using deterministic learning, and stored as constant RBF networks. In the recognition phase, a set of dynamical systems will be constructed by employing the modelling results. A set of estimation errors can be obtained and used to measure the similarity between the test ECG signal and the training ECG signals.

As well known, high-dimensional input will lead to the curse of dimensionality [27] of RBF networks. It is necessary to reduce the dimensionality of the 12-lead ECG signals in the premise that most of the information is retained. In fact, 12-lead ECG and vectorcardiogram (VCG) can be linearly transformed into each other without loss of useful information content pertaining to the cardiac electrical activity. Based on this fact, we will first transform the 12-lead ECG signal into the three-dimensional VCG signal (denoted as TVCG to distinguish it from the VCG measured directly from the body surface) through an algorithm proposed in [28]. Then the TVCG signal is used for identity recognition.
Training phase

For the three-dimensional TVCG signal, the dynamical system can be represented as follows:

$$\dot{V}(t) = F(V(t)) \quad (9)$$

where $V(t) = [v_1(t), v_2(t), v_3(t)]^T$ represents the TVCG signal, $F(V(t)) = [f_1(V(t)), f_2(V(t)), f_3(V(t))]^T$ is the system dynamics, an unknown function vector.

In order to model the system dynamics $F(V(t))$ of (9), the following state estimator is employed:

$$\dot{\hat{V}}(t) = -(\hat{V}(t) - V(t)) + \hat{W}^T S(V(t)) \quad (10)$$

where $\hat{V}(t)$ is the estimation of $V(t)$, $A = \text{diag}(a_1, a_2, a_3)$ is a diagonal matrix, $a_i$ are design constants, $\hat{W} S(V(t))$ is RBF networks and is used to approximate the system dynamics $F(V(t))$. The following update law is used to update the weight estimates $\hat{W}$:

$$\dot{\hat{W}} = -\Gamma(S(V(t))V(t) + \sigma \hat{W}) \quad (11)$$

where $\Gamma = \Gamma^T > 0$, $\sigma > 0$ is a small parameter, and $V(t) = \hat{V}(t) - V(t)$.

It can be proved from the dynamical model (9), the state estimator (10) and the weight update law (11) that:

1. the state estimation error $\dot{V}(t)$ converges to zero;
2. $F(V(t)) = \hat{W}^T S(V(t)) + e$, where $\hat{W}$ is a constant vector computed from $\hat{W}$ according to the same averaging procedure as described in deterministic learning, $e$ is the modelling error.

That is, accurate modelling and time-invariant representation (i.e., $\hat{W}^T S(V(t))$) of TVCG dynamics are achieved. The modelling results of a TVCG signal of one recording taken from the PTB database are shown in Figure 1 as an example, where Figure 1(d) is the three-dimensional graph of the modelling result of the TVCG dynamics.

Recognition phase

Based on the time-independent representation of the training TVCG signals (constant RBF networks), a mechanism for ECG-based identity recognition will be proposed in the subsection. Let us consider a training set containing dynamical patterns $V^k$, $k = 1, \ldots, M$ with the
Using the time-invariant representation \( \mathbf{W} \) from the PTB database, patient116/s0302lrem, based on a training set containing six ECG signals taken from the 12-lead ECG signal is generated from

\[
\dot{V}^k(t) = F(V^k(t))
\]

(12)

For a test 12-lead ECG signal \( E(t) \), it is first transformed into a three-dimensional TVCG signal \( V_T(t) \) in the training phase. For the \( k \)th (\( k = 1, 2, \ldots, M \)) training TVCG signal \( V^k \), a dynamical model is constructed by using the time-invariant representation \( \mathbf{W}^k S(V_T) \) as

\[
\dot{\mathbf{V}}^k = -B(\mathbf{V}^k - V_T) + \mathbf{W}^k S(V_T)
\]

(13)

where \( \mathbf{V}^k \) is the system state, \( V_T = [v_{T1}, v_{T2}, v_{T3}]^T \) is the state of the test TVCG signal, \( B = \text{diag}(b_1, b_2, b_3) \), \( b_i (i = 1, 2, 3) \) are design parameters that are kept the same for all training TVCG signals.

Then, corresponding to the test TVCG signal \( V_T \) and the dynamical model (13) (for training TVCG signal \( V^k \)), we obtain the following recognition error system:

\[
\dot{\mathbf{V}}^k = -B \mathbf{V}^k + \mathbf{W}^k S(V_T) - F(V_T)
\]

(14)

where \( \mathbf{V}^k = \mathbf{V}^k - V_T \) is the state-tracking error.

It can be inferred from Theorem 2 in [22] that the state-tracking error \( \mathbf{V}^k \) is approximately proportional to the differences between the dynamics of the test TVCG signal and of the training TVCG signals. Therefore, the state estimation errors \( \mathbf{V}^k \) can be used for identity recognition. Based on the above analysis, an identity recognition mechanism based on the 12-lead ECG signal is given as follows:

- **Step 1.** Transformation of the 12-lead ECG signals of the training set into three-dimensional TVCG signals, and modeling the dynamics of the training TVCG signals \( V^k \), (\( k = 1, 2, \ldots, M \)).
- **Step 2.** Construction of a bank of state estimators as (13) by employing the RBF networks \( \mathbf{W}^k S(V_T) \) for the training TVCG signals \( V^k \).
- **Step 3.** Transformation of the test 12-lead ECG signal into a TVCG signal and taking it as input of the RBF networks to the dynamical models (13). A bank of errors \( \mathbf{V}^k \) is obtained and measured by its \( L1 \) norm \( \| \mathbf{V}^k \|_{L1} \).
- **Step 4.** The test TVCG can be recognized in accordance with the smallest \( \| \mathbf{V}^k \|_{L1} \) and then the recognition of the subject can be achieved.

As an example, a test ECG signal patient251/s0506 rem taken from the PTB database is recognized based on a training set containing six ECG signals taken from the PTB database, patient116/s0302lrem, patient180/s0374lrem, patient182/s0308lrem, patient236/s0462 rem, patient240/s0468 rem and patient251/s0506 rem. The average \( L1 \) norms of \( \mathbf{V}^k \), (\( k = 1, \ldots, 6 \)) for the six training ECG signals are shown in Figure 2. It is seen that patient251/s0503 rem is most similar to patient251/s0506 rem.

To show the discriminating ability of the dynamics, the dynamics of two TVCG signals taken from two patients, one myocardial ischemia patient and one healthy subject from the PTB database, are shown in Figure 3. It can be seen that the dynamics of different TVCG signals from the same subject, especially the healthy subject, are similarly with each other. On the other hand, two examples are given in Figure 4 to show the difference of dynamics between TVCG signals from different subjects. The dynamics of two TVCG signals from two myocardial ischemia patients and two healthy subjects are given in Figures 4(a) and (b), respectively. It can be seen that the TVCG dynamics difference between different subjects is apparently larger than between different recordings of the same subject. These indicate that the method would be more efficient and reliable for identity recognition.

**Results and discussion**

To evaluate the performance of the proposed methods, three experiments are conducted based on the 14 healthy subjects, the 99 subjects with various heart diseases and all the 113 subjects, respectively. Each experiment consists of three sub-experiments:

- One recording randomly selected from each subject is used as a test pattern; the remaining recordings are used as training patterns.
One recording randomly selected from each subject is used as a test pattern, another recording randomly selected from each subject is used as a training pattern, without considering the time interval length between the training and the test recording; one recording randomly selected from each subject is used as a training pattern, the remaining recordings are used as test patterns.

Tables 2–4 give the results of the three experiments, respectively. Thereinto, the accuracy is defined as, \[ \text{Accuracy} = \frac{CN}{TN} \times 100 \%, \] where \( CN \) and \( TN \) are the number of correctly recognized ECG signals and the test ECG signals, respectively. Accuracy of 100% is achieved for 14 healthy subjects; accuracy of 96.0% is achieved for 99 subjects with various diseases; accuracy of 95.6% is achieved for the combination of the 14 healthy subjects and 99 patients.

To further estimate the performance of the proposed method, a k-fold cross-validation method is used in the following experiment. It is a standard technique in machine learning and is popular for estimating the generalization ability of a classifier. In this paper, a 4-fold cross-validation is used to further estimate the proposed method, while, depending on the number of recordings of each subject, it is not a standard \( k \)-fold cross-validation. We put together the subjects with RN (RN = 2, 3, 4, 5, 7) recordings as a subset \( S_{RN} \), and the RN recordings of each subject in the subset are placed into RN subsets \( S_{RN} \).

Table 2. Results from the first experiment.

| Sub-experiment | Training | Test | Correct | Accuracy (%) |
|----------------|----------|------|---------|--------------|
| (a)            | 27       | 14   | 14      | 100.0        |
| (b)            | 14       | 14   | 14      | 100.0        |
| (c)            | 14       | 27   | 26      | 96.3         |
| Average result |          |      |         | 98.3         |

Table 3. Results from the second experiment.

| Sub-experiment | Training | Test | Correct | Accuracy (%) |
|----------------|----------|------|---------|--------------|
| (a)            | 232      | 99   | 95      | 96.0         |
| (b)            | 99       | 99   | 93      | 93.9         |
| (c)            | 99       | 232  | 211     | 91.0         |
| Average result |          |      |         | 93.3         |

Table 4. Results from the third experiment.

| Sub-experiment | Training | Test | Correct | Accuracy (%) |
|----------------|----------|------|---------|--------------|
| (a)            | 259      | 113  | 108     | 95.6         |
| (b)            | 113      | 259  | 107     | 94.7         |
| (c)            | 113      | 259  | 235     | 90.7         |
| Average result |          |      |         | 92.8         |
Table 5. Results of the 4-fold cross-validation.

| Fold | Training set | Test set | Correct | Accuracy (%) |
|------|--------------|----------|---------|--------------|
| 1    | 259          | 113      | 107     | 94.7         |
| 2    | 259          | 113      | 105     | 92.9         |
| 3    | 232          | 86       | 84      | 97.7         |
| 4    | 164          | 52       | 52      | 100.0        |
| Average result | | | | 96.3         |

$(l = 1, 2, \ldots, \text{RN})$, respectively. In the fold 1, the test set contains subsets $S_2, S_3, S_4$, $S_5$, and the remaining subsets are used as a training set. In the fold 2, the test set contains subsets $S_2, S_3, S_4$, $S_5$ and $S_1$, and the remaining subsets are used as a training set. In the fold 3, the test set contains subsets $S_2, S_3, S_4$, $S_5$, and the remaining subsets, except subset $S_2$, are used as a training set. In the fold 4, the test set contains subsets $S_1, S_2, S_3$, $S_5$, and the remaining subsets, except subsets $S_2$ and $S_1$ are used as a training set. The accuracy of the 4-fold cross-validation is 96.3%. Detailed results are given in Table 5.

From the experimental results, it can be seen that the recognition accuracies based on the 14 healthy subjects are better than those in the other two experiments. This may be attributed to the fact that the heart activity of the healthy subject is more stable than that of the subjects with various heart diseases. On the other hand, the recognition accuracies of the sub-experiment (c) of the three experiments are lower than those of the sub-experiments (a) and (b). Through careful analysis of the dynamics of each recording of each subject, we find that the shorter the time interval between two recordings, the more similar the system dynamics of the two recordings. It can be understood that the heart function is varying (or even declining) with time; accordingly, the system dynamics is also varying with time. This is a main reason that the accuracy of sub-experiment (c) is lower than that of the sub-experiments (a) and (b), as the time intervals between the randomly selected training signal and 2 or 3 (even 4) test signals measured from the same subject may be longer. In practice, the training set can be updated regularly to avoid the occurrence of error identity recognition. Moreover, the accuracy of the cross-validation is 96.3%, very similar to the accuracy (96.0%) of sub-experiment (c) of the third experiment. It shows that the proposed method has good generalization.

To show the advantage of the proposed method directly, Table 6 summarizes the experimental results of several methods for ECG-based identity recognition in literature. It can be seen that various features and techniques were used for identity recognition. In comparison, in the proposed method, ECG dynamics is used as a unique feature for identity recognition. The recognition accuracy for 14 healthy subjects from the PTB database is 100%, higher than the accuracy (92.9%) reported in [29]. The accuracies reported in [3,26,30] were also 100%, but there are some parameters to be set by trial and error; thus, their generalization will be limited. What is more, owing to the significant variation of ECG waveforms under different diseases, most of the existing methods are not evaluated by using patient subjects. For 113 subjects consisting of the 14 healthy subjects and 99 patients, the proposed method accuracy of 95.6% is achieved. To our best knowledge, the work in [13] and [31] are the only two studies that have discussed the ECG-based identity recognition in a cardiac irregularity condition, and accuracies of 96.42% and 99% were achieved, respectively. Although the accuracies reported in [13,31] are higher than the accuracy of the proposed method, the number of subjects (113 subjects) used throughout the paper is more than two times greater than that used in [13] (56 subjects, including 30 arrhythmia patients and 26 healthy subjects) and in [31] (50 subjects, including 32 arrhythmia patients and 18 healthy subjects).

Additionally, there are many methods evaluated by privacy databases. It is not possible to compare the proposed method with these methods directly. However,

| Reference | Sample number | Feature type | Technique | Accuracy |
|-----------|---------------|--------------|-----------|----------|
| Wang et al. [3] | 13 HS, ptbdb+13 HS, nsrdb | MF, AF | RDHB, WLFS, LDAC, kNN | 100.0% |
| Agrafioti and Hatzinakos [26] | 14 HS, ptbdb | ABF | AC, LDA, NNC, ED | 100.0% |
| Plataniotis et al. [29] | 14 HS, ptbdb | ABF | AC, DCT, NNC, ED GLLC, | 92.9% |
| Ghofrani et al. [30] | 12 HS, ptbdb | ARC, MPSD | kNN, MLP, PN | 100.0% |
| Agrafioti and Hatzinakos [13] | 30 mitdb+13ptbdb+13 nsrcdb | ABF | LDA, ED, PCA, CD, kNN | 96.4% |
| Singh and Gupta [31] | 32 mitdb+18 nsrcdb | MF | CTPCH, PPCC | 99.0% |
| Proposed | 14 HS, ptbdb | dynamics | DL | 100.0% |
| | 99 PS, ptbdb | dynamics | DL | 96.0% |
| | 14 HS+99 PS, ptbdb | dynamics | DL | 95.6% |

Note: ABF, autocorrelation based features; AC, autocorrelation; AF, analytic feature; ARC, autoregressive coefficients; CD, cosine distance; CTP, correlation-based template matching; DCT, discrete cosine transform; DL, deterministic learning; ED, Euclidean distance; GLLC, Gaussian log-likelihood classifier; HS, healthy subject; kNN, k nearest neighbours; LDA, linear discriminant analysis; LDAC, LDA classifier; MF, morphological feature; mitdb, MIT-BIH arrhythmia database; MLP, multi-layer perceptron; MPSD, mean power spectral density; NNC, nearest neighbor classifier; NN, neural network; nsrdb, MIT-BIH normal sinus rhythm; PCA, principal component analysis; PD, Privacy database; PNN, probabilistic neural network; PPCC, Pearson product-moment correlation coefficient; PS, patient subject; ptbdb, PTB database; RDHB, reduced-dimension heart beat (via PCA or LDA); WLFS = Wilks’ Lambda feature selection.
the generalizations of these methods are limited, since they are a combination of various techniques and there are some parameters that need to be set by trial and error. In the proposed method, the similarity between ECG signals is defined based on the ECG dynamics and measured by the state estimation errors and it is not needed to extract any feature from the test ECG. Thus, its generalization would be better than that of other methods.

There are, however, some limitations in the study. First, the measurement of the 12-lead ECG signal is not convenient in practical systems of human recognition. Second, the ECG signal is easily disturbed by various factors which will affect the recognition accuracy. Third, with the increase of the number of training ECGs, although the recognition accuracy will be improved, the recognition speed will be influenced. In the future work, we will improve the lead system to solve the convenience problem, and improve the recognition system in order to solve the speed problem.

Conclusions

In this study, a novel ECG-based method is proposed for identity recognition via deterministic learning. The dynamics of ECG signal is used as a unique feature for identity recognition. To measure the similarity between the test ECG signal and training ECG signals based on the dynamics, a set of dynamical systems is first constructed by employing the modeling results of training TVCG signals. A set of state estimation errors can be obtained by comparing the test TVCG signal with the dynamical models and used as the similarity measure. The experimental results indicate that it is more suitable for ECG-based identity recognition. Despite its limitations, the approach is valuable in that it is the first time the dynamics of the ECG signal are used for identity recognition and it provides a novel train of thought for biometric features recognition.

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References

[1] Gahi Y, Lamrani M, Zoglat A, et al. Biometric identification system based on electrocardiogram data. In: Aggarwal A, Badra M, Massacci F, editors. New technologies, mobility and security; Proceedings of NTMS’2008 Conference and Workshops (NTMS’08); 2008 Nov 5–7; Tangier, Morocco. IEEE; 2008. p. 1–5.
[2] Fratini A, Sansone M, Bifulco P, et al. Individual identification via electrocardiogram analysis. BioMed Eng OnLine. 2015 [cited 2017 Jun 10];14(1):78. DOI:10.1186/s12938-015-0072-y
[3] Wang Y, Agrafioti F, Hatzinakos D, et al. Analysis of human electrocardiogram for biometric recognition. EURASIP J Adv Signal Process. 2007 [cited 2017 Jun 10];2008(1):148658. DOI:10.1155/2008/148658
[4] Chirillo J, Blaul S. Implementing biometric security. Boston (MA): Hungry Minds, Inc; 2003.
[5] Hoekema R, Uijen GJ, Van Oosterom A. Geometrical aspects of the interindividual variability of multilead ECG recordings, IEEE Trans Biomed Eng. 2001;48(5):551–559.
[6] Odinaka I, Lai P-H, Kaplan AD, et al. ECG biometric recognition: A comparative analysis. IEEE Trans Inform Forensic Secur. 2012;7(6):1812–1824.
[7] Israel SA, Irvine JM, Cheng A, et al. ECG to identify individuals. Pattern Recognit. 2005;38(1):133–142.
[8] Biel L, Pettersson O, Philipson L, et al. ECG analysis: a new approach in human identification. IEEE Trans Instrum Meas. 2001;50(3):808–812.
[9] Wuebbeler G, Bousseljot R, Kreiseler D, et al. Human verification by heart beat signals. In: Working group 8.42. Berlin: Physikalisch-Technische Bundesanstalt (PTB); 2004.
[10] Irvine JM, Israel SA. A sequential procedure for individual identity verification using ECG. EURASIP J Adv Signal Process. 2009 [cited 2017 Jun 10];2009:243215. DOI:10.1155/2009/243215
[11] Irvine J, Wiederhold B, Gawston L, et al. Heart rate variability: a new biometric for human identification. In: Proceedings of the International Conference on Artificial Intelligence (IC-AI01); Jun 25–28; Las Vegas. New York (NY): CSREA Press; 2001, pp. 1106–1111.
[12] , Kyoso M, Uchiyama A. Development of an ECG identification system. In: Engineering in medicine and biology society. Proceedings of the 23rd Annual International Conference of the IEEE, vol. 4; 2001 Oct 25–28; Istanbul, Turkey, Piscataway (NJ): IEEE; 2001, p. 3721–3723.
[13] Agrafioti F, Hatzinakos D. ECG biometric analysis in cardiac irregularity conditions. SIIVIP. 2009;3(4):329–343.
[14] Fang S-C, Chan H-L. Human identification by quantifying similarity and dissimilarity in electrocardiogram phase space. Pattern Recognit. 2009;42(9):1824–1831.
[15] Safie SJ, Saroghan JJ, Petropoulakis L. Electrocardiogram (ECG) biometric authentication using pulse active ratio (par). IEEE Trans Inform Forensic Secur. 2011;6(4):1315–1322.
[16] Shen T-W, Tompkins WJ, Hu YH. Implementation of a one-lead ECG human identification system on a normal population. J Eng Comput Innov. 2011;2(1):12–21.
[17] Dong X, Wang C, Hu J, et al. Electrocardiogram (ECG) pattern modeling and recognition via deterministic learning. Control Theory Technol. 2014;12(4):333–344.
[18] Wang C, Dong X, Ou S, et al. A new method for early detection of myocardial ischemia: cardiodynamicsgram (CDG). Sci China Inf Sci. 2016;59(1):1–11.
[19] Wang C, Hill DJ. Deterministic learning theory for identification, recognition, and control. Boston (MA): CRC Press; 2009.
[20] Wang D. Temporal pattern processing. In: Arbib MA, editor. The handbook of brain theory and neural networks. Cambridge (MA): MIT Press; 2003. p. 1163–1167.

[21] Hong P, Huang TS. Automatic temporal pattern extraction and association. In: IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), 2002. Proceedings, vol. 2; 2002 May 13–17; Orlando (FL). IEEE; 2002. p. II–2005.

[22] Wang C, Hill DJ. Learning from neural control. IEEE Trans Neural Netw. 2006;17(1):130–146.

[23] Wang C, Hill DJ. Deterministic learning and rapid dynamical pattern recognition. IEEE Trans Neural Netw. 2007;18 (3):617–630.

[24] Goldberger AL, Amaral LA, Glass L, et al. Physiobank, physiotoolkit, and physionet components of a new research resource for complex physiologic signals. Circulation. 2000;101(23):e215–e220.

[25] Lines G, Buist M, Grottum P, et al. Mathematical models and numerical methods for the forward problem in cardiac electrophysiology. Comput Visualiz Sci. 2003;5(4):215–239.

[26] Agrafti F, Hatzinakos D. Fusion of ECG sources for human identification. In: 3rd International Symposium on Communications, Control and Signal Processing, 2008 (ISCCSP 2008); Proceedings. 2008 Mar 12–14; St. Julians, Malta. Piscataway (NJ): IEEE; 2008. p. 1542–1547.

[27] Haykin SS. Neural networks: a comprehensive foundation. Beijing: Tsinghua University Press; 2001.

[28] Kors J, Van Herpen G, Sittig A, et al. Reconstruction of the frank vectorcardiogram from standard electrocardiographic leads: diagnostic comparison of different methods. Eur Heart J. 1990;11(12):1083–1092.

[29] Plataniotis KN, Hatzinakos D, Lee JK. ECG biometric recognition without fiducial detection. In: 2006 Biometrics Symposium: Special Session on Research at the Biometric Consortium Conference. 2006 Sep 19–21; Baltimore (MD). IEEE; 2006. p. 1–6. DOI:10.1109/BCC.2006.4341628

[30] Ghofrani N, Bostani R. Reliable features for an ECG-based biometric system. In: 17th Iranian Conference of Biomedical Engineering (ICBME); Proceedings. 2010 Nov 3–4; Isfahan (Iran). IEEE; 2010. p. 1–5. DOI:10.1109/ICBME.2010.5704918

[31] Singh YN, Gupta P. Correlation-based classification of heartbeats for individual identification. Soft Comput. 2011;15(3):449–460.