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Extracting cardiac dynamics within ECG signal for human identification and cardiovascular diseases classification

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ABSTRACT

Cardiac characteristics underlying the time/frequency domain features are limited and not comprehensive enough to reflect the temporal/dynamical nature of ECG patterns. This paper proposes a dynamical ECG recognition framework for human identification and cardiovascular diseases classification via a dynamical neural learning mechanism. The proposed method consists of two phases: a training phase and a test phase. In the training phase, cardiac dynamics within ECG signals is extracted (approximated) accurately by using radial basis function (RBF) neural networks through deterministic learning mechanism. The obtained cardiac system dynamics is represented and stored in constant RBF networks. An ECG signature is then derived from the extracted cardiac dynamics along the periodic ECG state trajectories. A bank of estimators is constructed using the extracted cardiac dynamics to represent the trained gait patterns. In the test phase, recognition errors are generated and taken as the similarity measure by comparing the cardiac dynamics of the trained ECG patterns and the dynamics of the test ECG pattern. Rapid recognition of a test ECG pattern begins with measuring the state of test pattern, and automatically proceeds with the evolution of the recognition error system. According to the smallest error principle, the test ECG pattern can be rapidly recognized. This kind of cardiac dynamics information represents the beat-to-beat temporal change of ECG modifications and the temporal/dynamical nature of ECG patterns. Therefore, the amount of discriminability provided by the cardiac dynamics is larger than the original signals. This paper further discusses the extension of the proposed method for cardiovascular diseases classification. The constructed recognition system can distinguish and assign dynamical ECG patterns to predefined classes according to the similarity of cardiac dynamics. Experiments are carried out on the FuWai and PTB ECG databases to demonstrate the effectiveness of the proposed method.

1. Introduction

Electrocardiogram (ECG) signal is one of the most commonly used vital signs in the healthcare engineering (Sansone, Fusco, Pepino, & Sansone, 2013). It provides an insight into the variation of bioelectric potential with respect to time as the human heart beats (Israel, Irvine, Cheng, Wiederhold, & Wiederhold, 2005; Odinaka et al., 2012). In the past decades, ECG pattern recognition has attracted increasing attention in both clinical and non-clinical applications, ranging from cardiovascular disease diagnosis (Beritelli, Capizzi, Sciuto, Napoli, & Scaglione, 2017; Martis, Acharya, Ray, & Chakraborty, 2011), human identification (Irvine, Israel, Scruggs, & Worek, 2008; Stavridis, Kreiseler, Bousseljot, & Elster, 2007; Sufi & Khalil, 2011), telemedicine (Costa & Oliveira, 2012; Jui-Chien & Meng-Wei, 2012), to home-care monitoring (Chung, Bhardwaj, Punvar, Lee, & Myllylae, 2007; Lobodzinski & Jadalla, 2010).

1.1. ECG for human identification

As regards ECG for human identification, several pioneering works (Biel, Pettersson, Philipson, & Wide, 2001; Israel et al., 2005) have confirmed the feasibility of ECG as an identifier of individuals. The temporal relationships and shapes of different ECG waves should be unique for each individual, consequently, ECG could be a powerful biometric for human identification. After these pioneering works, a vast literature has accumulated on this subject (Tantawi, Revett, Salem, & Tolba, 2014).

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Morphological and time–frequency descriptors constitute two most popular ECG features used in human identification (Sansone et al., 2013). Generally speaking, morphological descriptors are the intuitive shape features including height and duration of QRS, height of P-wave, height of T-wave and so on (M & A, 2009; Israel et al., 2005; Singh & Gupta, 2009,2011). Time–frequency descriptors are usually characterized by timing information (PR-interval, RR-interval, QT-interval, etc.) and time–frequency coefficients (wavelet coefficients, etc.) in the ECG cycle (Bao, Poon, Zhang, & Shen, 2008; Li & Narayanan, 2010; Odinaka et al., 2011). In Wang, Agrafioti, Hatzinakos, and Plataniotis (2007), analytic and appearance features were extracted as morphological features, and a two-step fiducial detection framework was introduced. In Tantawi et al. (2014), interval, amplitude and angle parameters were extracted as the morphological and time–frequency features to perform the person identification task. In Chan, Hamdy, Badre, and Badee (2008), wavelet distance measure was proposed as time–frequency descriptor for person identification. In Christov et al. (2006), Christov et al. presented a comparative study of morphological (QRS descriptors) and time–frequency (expansion coefficients) ECG descriptors for heartbeat classification. The experimental results indicated that, the accuracies of morphological and time–frequency descriptors are sufficiently high and do not show significant differences. More recently, techniques based on data-driven model (Adler, Elad, Hel-Or, & Rivlin, 2013; Carrera, Rossi, Zambon, Fragneto, & Boracchi, 2016; Kiranyaz, Ince, & Gabbouj, 2016) and KLT representation (Biagetti, Crippa, Curzi, & Orcioni, 2014; Crippa, Curzi, Falaschetti, & Turchetti, 2015) were developed for ECG signal processing.

Despite that much progress has been made for ECG human identification, so far, only limited success has been reported in the literature for direct recognition of temporal ECG patterns (Odinaka et al., 2012; Sansone et al., 2013). Most of the existing works only extract limited static descriptors within temporal ECG patterns, transforming the recognition problem of temporal ECG patterns into recognition of static patterns (Tantawi et al., 2014). Since cardiac characteristics underlying static descriptors are relatively limited and not comprehensive enough to reflect temporal (dynamical) nature of ECG patterns (Xiang & Chen, 2009), one possible method is to extract cardiac dynamics within ECG signal and present a novel, completely dynamical framework for temporal (dynamical) ECG pattern recognition. However, how to gain cardiac dynamics during a dynamical heart-beating process is an extremely challenging problem (Hong & Huang, 2002). Further, how to store the extracted cardiac dynamics in the training process and how to exploit the stored dynamics for human identification are also important problems in the pattern recognition community (Wang, 1995; Wang & Hill, 2007).

Fortunately, based on our previous works on system identification and dynamical pattern recognition (Deng, Wang, & Chen, 2016; Deng, Wang, Cheng, & Zeng, 2017; Wang & Hill, 2007, 2009; Zeng & Wang, 2012), these difficulties can be overcome by the following two steps: (1) by achieving the satisfaction of the persistent excitation (PE) condition for a recurrent trajectory (Wang & Hill, 2005), deterministic learning mechanism is able to capture the nonlinear dynamics underlying a time-varying dynamical pattern and represent dynamics information in a time-invariant manner, and (2) by using the concept of topological equivalence (Wang & Hill, 2007), a similarity definition for dynamical patterns is given based on the difference between the nonlinear dynamics of dynamical patterns. Compared with other results on approximation and convergence analysis of neural networks, e.g., the profound work of deep learning (Baldi & Sadowski, 2016; Schmidhuber, 2015), the works by Costarelli (Costarelli, 2015; Costarelli & Vinti, 2016a, b, c, d; Di, Forti, Grazzini, & Pancioni, 2014), we utilize more advanced concepts and theories from adaptive control and dynamical systems, such as the PE condition, recurrent trajectories, and topological equivalence. So far, the deterministic learning algorithm has been applied successfully to gait recognition (Deng et al., 2016, 2017; Zeng & Wang, 2012) and oscillation faults diagnosis (Chen, Wang, & Hill, 2014; Wang & Chen, 2011).

Following this idea, in this paper, we attempt to propose a dynamical neural learning mechanism for extracting the cardiac dynamics within ECG signal based on deterministic learning algorithm. The final goal of this paper is to reuse these cardiac dynamics to represent ECG patterns for further human identification. This kind of dynamics information represents the beat-to-beat temporal change of electrophysiological modifications, which is shown to be useful and sensitive for human identification and cardiovascular disease diagnosis.

1.2. Outline of the proposed method

As schematically shown in Fig. 1, the proposed method consists of two phases: a training (dynamics acquisition) phase and a test (dynamics reuse) phase. Standard 12-lead ECG signal is collected to characterize the cardiac system dynamics. Since twelve-dimensional ECG signals and three-dimensional vectorcardiogram (VCG) signals (Dower, Machado, & Osborne, 1980) can be linearly transformed into each other without loss of information content pertaining to the cardiac dynamics, the cardiac system dynamics can be simplified to be described by the beat-to-beat temporal change of VCG signals, thus the input dimension is effectively reduced.

In the training phase, locally-accurate identification (approximation) of the cardiac system dynamics underlying VCG signals is achieved by using radial basis function (RBF) neural networks through deterministic learning. A partial PE condition of the regression subvector constructed out of the RBFs is satisfied along the recurrent VCG trajectories. The satisfaction of partial PE condition guarantees that neural weights of the RBF networks will exponentially converge to optimal values. The obtained cardiac dynamics is stored in constant RBF networks for reusing in later human identification task. In this sense, time-varying ECG dynamical patterns can be effectively represented as the locally accurate neural network approximations of cardiac dynamics, in a time-invariant manner (constant RBF networks).

In the test phase, a bank of estimators is constructed to represent the trained ECG patterns by using the previously extracted cardiac system dynamics. By comparing the test ECG pattern with the set of estimators, a set of recognition errors is generated, and the average L_1 norms of the errors are taken as the similarity measure between the dynamics of the test ECG pattern and the dynamics of the trained ECG patterns. Based on the smallest error principle, the appearing test person can be recognized as one of the trained patterns rapidly.

1.3. Contributions of the proposed paper

Compared with other results on ECG human identification, the contributions of this paper lie in the following aspects:

- A novel, completely dynamical framework is proposed for temporal (dynamical) ECG pattern recognition without static feature extraction. Cardiac dynamics underlying standard 12-lead ECG signal is extracted by using a dynamical neural learning mechanism, representing the beat-to-beat temporal change of ECG modifications and the temporal (dynamical) nature of ECG patterns. Rapid recognition of a test ECG pattern begins with measuring the state of test pattern, and automatically proceeds with the evolution of the recognition error system. The whole recognition process does not need any numerical computation for feature extraction or feature matching.