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Individualization of a vectorcardiographic model by a particle swarm optimization

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ABSTRACT

This paper presents the application of a bio-inspired method for optimizing a lifelike vectorcardiographic (VCG) model. During the model estimation, a Particle Swarm Optimization (PSO) seeks the optimal combination of all parameters that maximize the correlation coefficient (r) and minimize the Mean Squared Error (MSE) between the synthetic and directly measured VCG leads. The proposed method was tested on 52 different VCG records annotated as a healthy control (HC) from PTB database. 156 models were individualized without any previous analysis of the waves of the original records. The PSO method automatically provides very realistic models with a correlation coefficient $r > 0.995$ and MSE < 0.0005 mV^2 for 152 of the 156 VCG signals.

1. Introduction

Electrocardiography (ECG), one of the most important diagnostic tools used in clinical cardiology, is based on measuring the electrical activity of the heart from the surface of the human body. The most common recording method consists of 12 leads which correspond to projections of electrical activity to different directions in the cardiac space. During the cardiac cycle, electrochemical processes, called depolarisation and repolarisation, of the cardiac cells occur in a particular region of the heart. These processes cause individual patterns called P, Q, R, S, T, and occasionally present a U wave in electrocardiograms (ECG).

The basic mathematical model describing the cardiac cycle is based on a moving dipole (MD). MD is a resulting vector of the electromotive forces of the individual cardiac cells during cardiac activity [9]. This vector is represented by 3 orthogonal components and time. The direct measurement of these components is the basis of vectorcardiography (VCG). Three orthogonal leads X, Y and Z are measured as projections into three orthogonal directions [1,8].

MD describes the magnitude and direction of the de/repolarisation waves in cardiac muscle and in three-dimensional space and is represented in the form of P, QRS and T loops [8]. Conventional ECG leads are computed from this model using the transformation method. The relationship between ECG and VCG can be described by a transformation matrix. The most common methods are inverse Dower and Kors transformation which differ only in the coefficients of the matrix [2].

An approximation of the MD can be used for generating a realistic artificial ECG/VCG. These artificial signals are used in many areas of biomedical research. The most common use is for testing new algorithms in pre-processing (filtration, segmentation), compression and analysis of the ECG [5,6]. New algorithms for classifying ECG patterns [16] are usually tested on real records and an annotation of the data is required. For example, for 24-h records, a Holter monitor can collect more than hundreds of thousands beats, which are impossible to analyse manually and comparing new algorithms will only be possible with existing methods. However, with a synthetic ECG generator, it is possible to generate long realistic records with a known annotation that includes all possible pathologies and artefacts [4].

It is also possible to generate variances in the ECG with the model, such as an abnormal cardiac rhythm, respiration effects, ectopic beats and artefacts [7]. Pathological changes, such as myocardial infarction (MI), hypertrophy etc. are reflected as changes to the shape and intervals of the individual waves or segments in the ECG. One cardiac cycle of the model can be individualized to an actual ECG/VCG record by using the approximation model [3].

The Gaussian function is the most common way to approximate individual waves [3–7]. Parameters of the Gaussian function

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then correspond to the shape of the resulting waves. For fitting of these parameters to real beats, a gradient descent method is used [4,7]. But this method requires a previous analysis of the ECG and the approximation often fails in some non-Gaussian shapes of the waves. However non-Gaussian shapes are common in ECG records, especially in pathology records. Precisely expressing the pathology in the model is crucial for further use of the model.

Non-symmetrical waves are often present even in healthy records, and this cannot be approximated with only one Gaussian function. Multiple Gaussian functions can approximate both non-symmetry and bipolar waves (often T waves). But the number of Gaussian functions needed for representing the entire beat varies depending on records and leads. For MI records, often elevation or depression of the ST segment is present in some leads. It is also possible to approximate using several Gaussian functions with specific parameters but the fitting process is complicated because there is no previous knowledge about the number and/or positions of the Gaussian functions.

This paper focuses on the design of an automatic method for identifying the positions and parameters of Gaussian functions to accurately approximate the MD without having any previous knowledge of the VCG record.

2. Materials and methods

2.1. Study population and preprocessing

Tested records were chosen from a PTB diagnostic database that was recorded from healthy volunteers and patients with different heart diseases at the Department of Cardiology of University Clinic Benjamin Franklin in Berlin, Germany. The database contains 549 records from 286 subjects. Each subject is represented by one to five records. Each record includes 15 simultaneously measured signals: the conventional 12 leads together with the 3 Frank VCG. Each signal was digitized at 1000 samples per second, with 16 bit resolution over a range of ±16.384 mV [11–13].

There are 52 records measured on different patients annotated as healthy control (HC) in the PTB. All these records were used to test of the proposed algorithm.

The records were band-passed using an FIR filter with a linear phase response in range from 0.5 to 150 Hz (−3 dB). From the filtered records, representative VCG beats excluding ectopic beats and artefacts were chosen. The beginning of the beat was defined as distance from the R wave: $T_R - 0.4T_{\min(RR)}$ and the end of beat was defined as $T_R + 0.6T_{\min(RR)}$, where T_R is the time of presence of an R wave and $T_{\min(RR)}$ is the minimal pulse period for the record. The positions of R waves were detected using Pan–Tompkins' algorithm [19] from a V signal (1). Individual representative beats were averaged for each VCG lead and then an isoelectric line was zeroed by subtracting the median value from each averaged beat.

$$V = \sqrt{X^2 + Y^2 + Z^2} \tag{1}$$

2.2. Vectorcardiographic model

In electrocardiology, models are used to describe potentials at electrodes placed on the thorax. The best-known model is a dipole model which is the basis of VCG. Other models are based on multipole expansions or double layer representation [8,9].

The MD is commonly referred to as the (time-dependent) heart vector $M(t)$. As each wave of de/repolarization spreads through the heart, the heart vector changes in magnitude and direction as a function of time [9,10]. MD $M(t)$ is given by three orthogonal components X_m, Y_m and Z_m. With each component, it is possible to approximate the sum of n Gaussian by the following functions:

$$\begin{aligned} X_m &= \sum_{i=1}^{n} a_i^x \cdot e^{-\left(\Delta\theta_i^x\right)^2/2\left(b_i^x\right)^2}, \\ Y_y &= \sum_{i=1}^{n} a_i^y \cdot e^{-\left(\Delta\theta_i^y\right)^2/2\left(b_i^y\right)^2}, \\ Z_y &= \sum_{i=1}^{n} a_i^z \cdot e^{-\left(\Delta\theta_i^z\right)^2/2\left(b_i^z\right)^2}, \end{aligned} \tag{2}$$

where $\Delta\theta_i^x = \theta_0 - \theta_i^x$ is the relative phase with phase $\theta_0 \in [0, 2\pi]$. Each Gaussian function is described by three parameters: amplitude a_i^x, width b_i^x and phase θ_i^x which corresponds to the position of the ith Gaussian function in the range from 0 to 2π in the lead X.

To fit the model to an observation, an optimization method should be performed to set the a_i, b_i and θ_i parameters.

2.3. Design of the objective function

The authors in [4,7] used a gradient descent method to fit the model to a real record. This method is based on minimizing the MSE between the model based X_m and the directly measured Frank lead X_F by the following equation:

$$\mathrm{MSE} = \frac{1}{n}\sum (X_m - X_F)^2. \tag{3}$$

A further important and common parameter indicating similarity between two signals is the Pearson correlation coefficient r. The correlation indicates the degree of similarity between two signals and is independent of the differences in their amplitudes

$$r = \frac{\sum (X_m X_F)}{\sqrt{\sum X_m^2 \sum X_F^2}} \tag{4}$$

For the purpose of optimizing the VCG models, the combination of these two parameters is used. The correlation can take values in range of $r \in [-1, 1]$ and $\mathrm{MSE} \geq 0$. For identical signals $r = 1$ and $\mathrm{MSE} = 0$. Both these parameters are combined in the objective function (5). When the objective function (5) is maximized, the MSE is also maximized and r is minimized at the same time.

$$G(r,\ \mathrm{MSE}) = r\frac{10^{1/(\mathrm{MSE}+1)}}{10}. \tag{5}$$

For identical signals $G = 1$. An optimization method looks for the optimal combination of the parameters by maximizing the objective in the following function:

$$\max_{a_i, b_i \theta_i} (G). \tag{6}$$

2.4. Fitting model to features

Each beat including P, Q, R, S and T waves, can be represented as the sum of n Gaussian functions. A demonstration of this principle is presented in Fig. 1. Each wave is formed by one Gaussian function. The number and position of Gaussian functions can easily be determined based on a previous analysis of the signal and the parameters a_i and b_i can be optimized using the gradient descent method.

Non-symmetrical and bipolar waves are always approximated using two or more Gaussian functions. Elevation/depression of the ST segment and other extra shapes such as a pathological R wave should be automatically recognized and approximated using multiple Gaussian functions. The optimal number of Gaussian functions varies in records, leads and individual waves. The maximal number