An Artificial Model of the Electrocardiogram during Paroxysmal Atrial Fibrillation

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Abstract

Introduction: We present an extension of an artificial ECG model for the simulation of multi-lead ECG during paroxysmal Atrial Fibrillation (AF).

Method: This new method was based on adaptation of previously published models, one which generates the cardiac dipole from a sum of Gaussian kernels and one which simulates atrial activity during AF by using a saw-tooth like shaped function. The proposed model also allows for the generation of ectopic beats. The generation of paroxysmal AF was made possible by the use of a multiple layer-based Hidden Markov Model (HMM). The first layer allowed for the switching between different rhythms (AF or normal sinus rhythm). The second layer enabled the simulation of short and long RR intervals, as AF is usually accompanied with the succession of short and long RR intervals. The values of the transition matrix were defined as described in the literature for realistic AF rhythmicity. The final HMM layer allowed for the simulation of ectopic beats independently of the rhythm. The cardiac dipole was then generated with a sum of Gaussian kernels appropriate to the beat type. During AF, the Gaussians for the P wave were replaced by the saw-tooth like atrial activity function. Each parameter of the different models was allowed to evolve stochastically to simulate the inherent non-stationarity of a physiological signal. Finally, physiological noise extracted from the noise-stress database were added to enhance the realism of the simulation.

Results: The model was first visually inspected in order to assess its realism. State-of-the-art RR interval based AF detection and atrial activity techniques were applied on the simulated signals and results were compared to the literature. AF detection results were lower than those reported in the literature (Se=62%), but atrial activity extracted were in accordance with previously published results.

Discussion: The simulation of ECG signal with paroxysmal AF provides a framework for quantitative assessment of any atrial activity extraction technique, and is useful for preliminary validation before application on real ECG data, or evaluation on rare events that can be simulated instead.

1. Introduction

Atrial Fibrillation (AF) is one of the most common cardiovascular pathologies with its high prevalence in the general population (0.4% to 1%), which is increasing as societies age [1]. AF is a heart rhythm abnormality and is associated with an increased risk of stroke and heart failure, especially in women [1]. However, it remains challenging to diagnose this pathology, as it is an asymptotic disease and is commonly detected only after the patient presents one of the serious complications of AF, such as stroke and heart failure [2].

Several processing techniques have been recently developed in order to automatically detect AF episodes in an ECG signal. These techniques have been designed to use two main characteristics of AF, (1) random firing of the AV node yielding highly irregular tachograms [3-5], (2) fibrillation of the atria yielding to the suppression of the P-waves and the presence of a continuous depolarization of the atria, which manifest as small oscillations on the ECG, called f-waves [6, 7].

These processing techniques have been developed and tested on publicly available databases, such as the MIT-BIH arrhythmia and AF databases [8, 9]. Such databases offer many advantages, including the possibility of testing and comparing different algorithms on the same datasets, which have been previously annotated by multiple experts. Nevertheless, they also present some drawbacks, for AF detection since these databases contain no recording with ECG of paroxysmal AF with short episodes, or the ground-truth of the atrial activity is not known/ Therefore assessing the quality of an atrial activity extraction algorithm difficult.

In this paper, we present an extension of an artificial ECG model for the simulation of a multi-lead ECG signal during paroxysmal AF.

2. Method

The proposed model is based on two previously published models, the first one simulating the ECG signal [10, 11], and the second one simulating the saw-tooth like f-waves [6, 7]. A third model, the multiple layer-based Hidden Markov Model (HMM), was implemented to generate realistic RR interval time-series with episodes of AF. These three models, and their combination are now described.

2.1. Dynamic VCG model

The ECG signal has previously been accurately described as a pseudo-periodic signal, whose cycle is a sum of Gaussian waves [10]. This model has paved the way for a range of applications, and was extended for the simulation of ECG signals with T-Wave Alternans, developed for the Physionet-CinC Challenge 2008 [11]. In this model, the cardiac activity is simulated by using a single dipole approximation, whose Cartesian dynamics $\boldsymbol{d(t)} = x(t)\hat{a}_x + y(t)\hat{a}_y + z(t)\hat{a}_z$ can be modeled as:

$$\dot{\theta} = \omega$$

$$\dot{x} = -\sum_i \frac{\alpha_i^x \omega}{\left(b_i^x\right)^2} \Delta\theta_i^x \exp\left[-\frac{\left(\Delta\theta_i^x\right)^2}{2\left(b_i^x\right)^2}\right]$$

$$\dot{y} = -\sum_i \frac{\alpha_i^y \omega}{\left(b_i^y\right)^2} \Delta\theta_i^y \exp\left[-\frac{\left(\Delta\theta_i^y\right)^2}{2\left(b_i^y\right)^2}\right]$$

$$\dot{z} = -\sum_i \frac{\alpha_i^z \omega}{\left(b_i^z\right)^2} \Delta\theta_i^z \exp\left[-\frac{\left(\Delta\theta_i^z\right)^2}{2\left(b_i^z\right)^2}\right],$$

where $\theta \epsilon [-\pi, \pi]$ is the cardiac phase $\Delta\theta_i^j = (\theta - \theta_i^j) mod(2\pi), j \epsilon \{x, y, z\}, \omega = 2\pi h / (60\sqrt[\varsigma]{h_{av}})$, where h is the instantaneous heart rate in bpm, h_{av} is the average over the previous 6 beats normalized by 60bpm and the operation $\sqrt[\varsigma]{h_{av}}$ accounts for the Bazett or Fridericia correction (with $\varsigma = 2$ *or* 3 respectively).

The multi-channel ECG is then generated by propagating the dipole on the chest using the following equation: $\boldsymbol{ECG(t)} = H \cdot R \cdot \Lambda \cdot (\boldsymbol{d(t)} + \boldsymbol{w(t)})$, where $\boldsymbol{ECG(t)}$ is the vector of the *N* recorded channels, *H* is the inverse Dower transformation matrix, Λ is a scaling matrix and *R* is a continuously changing rotation matrix which allows for the simulation of respiration-based axes changes and baseline wander, and finally ***w(t)*** is the vector of realistic physiological noise taken from the Noise Stress Database [9].

2.2. f-wave model

The above model cannot be used to simulate AF, as atrial activity does not have the same periodicity as ventricular activity. For that purpose, we use the saw-tooth model developed by Stridh *et al.* [6] and Petrenas *et al.* [7]. This model can be expanded as a sum of sinusoidal functions as follows:

$$s_{atria}(t) = \sum_{m=1}^{M} a_m(t) \sin\left(m\omega_0 t + \frac{\Delta_f}{f_f}\sin(\omega_f t)\right),$$

where $\omega_0 = 2\pi f_0$, with f_0 being the fundamental frequency of the fibrillation waveform, has a maximum frequency deviation Δ_f and the modulation frequency is $\omega_f = 2\pi f_f$. The amplitude $a_m(t)$ is defined as:

$$a_m(t) = \frac{2}{m\pi}(a + \Delta a \sin(\omega_a t)),$$

where a is the amplitude parameter, Δa and ω_a are the amplitude modulation and modulation frequency.

The ECG model is built by using the dynamics of the waveforms. In order to combine these two models we also use the dynamics, $\partial s_{atria}(t)/\partial t$, for the atrial activity in case of AF.

The different parameters for the atrial fibrillation activity were allowed to evolve with time by considering them as random variables set as follows: $f_0 = \mathcal{N}(6,0.1), \Delta f = \mathcal{N}(0.25,0.01)$, $f_f = \mathcal{N}(0.1,0.005)$, $\boldsymbol{a} = \mathcal{N}([0.015\ 0.0075\ 0.0045], [0.001\ 0.001\ 0.001])$, $\Delta a = \mathcal{N}(0.005,0.0003)$, $f_a = \mathcal{N}(0.008,0.002)$. These values were set according to [7].

Moreover, the model described in [7] was enhanced by adding stochastic noise for increased realism. Random coloured noise was therefore added to the dynamics of the atrial activity as follows:

$d_a(t) = \partial s_{atria}(t)/\partial t + \omega_c(t)$, where $\omega_c(t)$ is a Gaussian white noise coloured by filtering with a first derivative and 2nd order Butterworth band-pass filter with a [0.05,60] band-pass frequency.

2.3. RR interval generation

Before applying the equations described above, a realistic RR interval time-series must be generated. Accurate modelling of the random firing of the AV node during AF must be simulated. A multiple layer-based HMM was chosen for that purpose.

First, the base RR interval time-series was generated as per McSharry *et al.* [10]. This model allows for the generation of RR intervals, with a bimodal spectrum simulating parasympathetic high frequency (HF) and the sympathetic (LF) heart rate modulation. The parameters of the model were chosen as follows: the baseline heart rate was set to 70bpm, with a heart standard deviation of 5bpm and a LF/HF ratio of 2.

2.3.1. Generation of AF episodes

The aim of this study was the simulation of an ECG signal during paroxysmal AF, and therefore the transition between normal rhythm and AF episodes needs to be simulated. This transition was simulated in a probabilistic framework using a first-order Markov chain, with a HMM.

Each cardiac beat can then be in either the normal rhythm state or in an AF episode state. The transition between each state is be governed by a State Transition Matrix (STM) defined as:

$$STM = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix},$$

where p_{ij} represents the probability of a transition from the state j to the state i:

$$p_{ij} = P(State(t) = i | State(t-1) = j).$$

2.3.2. Generation of arrhythmias

After this first HMM layer, each beat is classified as a normal beat or an Atrial Fibrillation beat. The model of AF requires the simulation of the randomness of the RR interval time-series during AF episodes.

Moody and Mark have suggested an HMM-based approach for detecting AF by using RR intervals [12]. This HMM technique was reversed and used for the generation of AF-like RR intervals. In their work, Moody and Mark estimated the transition state matrices between short regular and long RR intervals on the MIT-BIH arrhythmia database [8.12]. Two matrices were estimated, the first one for simulating the transitions during AF and the second one simulating the same transitions during other rhythms. These matrices are given by:

$$STM_{SRL\{AF\}} = \begin{bmatrix} 0.25 & 0.11 & 0.15 \\ 0.51 & 0.74 & 0.65 \\ 0.24 & 0.15 & 0.20 \end{bmatrix} \text{ and}$$

$$STM_{SRL\{other\}} = \begin{bmatrix} 0.21 & 0.02 & 0.21 \\ 0.21 & 0.96 & 0.48 \\ 0.59 & 0.02 & 0.31 \end{bmatrix}.$$

State 1 represents a short RR interval, state 2 a regular RR interval, and state 3 represents a long RR interval.

Once a beat is attributed the state 1, its RR value is multiplied by a factor $\alpha = \mathcal{N}(0.66, 0.02)$. If a beat is attributed the state 3, its RR value is multiplied by a factor $\beta = \mathcal{N}(1.33, 0.02)$. State 2 RR intervals remain unchanged.

2.3.3. Generation of ectopic beats

Finally, another HMM layer was added in order to generate premature ventricular contractions or ectopic beats. The choice for a separate HMM was motivated by the fact that such beats can occur independently from the dominant rhythm, That is ectopic beats also occur during AF.

2.4. Quality assessment of the model

The simulated signals were first qualitatively evaluated by visually inspecting the realism of both morphology of the waveforms and the RR interval time-series.

Quantitative assessment of the realism of the simulation was performed in two different ways. First, an RR interval-based AF detector was applied on the simulated RR interval time-series [3] and results were compared with those obtained by the method on the MIT-BIH arrhythmia database [8]. This detector is based on the sample entropy and was optimized for detecting short episodes of AF on a small window length (12). 1000 windows were generated, with 414 containing an AF episode. Finally, an atrial activity extraction method based on a Echo State Neural Network was applied on the simulated signals and results obtained were compared to those reported in the literature [7].

3. Results

1 shows an example of the simulation of ECG during paroxysmal AF. The transition between AF and normal rhythm can be observed at the 50th and the 70th second. An ectopic beat has also been simulated around the 63th second, during AF. The noise was also generated in order to simulate a 3dB SNR, this noise level can be observed on the top row.

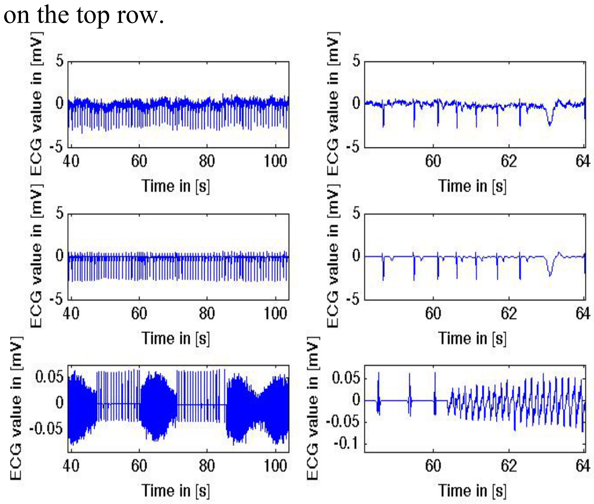

Figure 1: Example of a simulation of an ECG with paroxysmal AF. The top row contains the simulated ECG with ventricular and atrial activity and the noise. The middle row contains the clean ventricular activity. The bottom row contains the atrial activity only. The left and right columns are views from different segments of the simulated signals with different time windows.

The AF detector obtained a sensitivity of 62% and accuracy of 50%, which is well below the results reported in [5].

An Echo-state neural network based method for extracting atrial activity has been applied on simulated signals and the Signal to Noise Ratio (SNR) and Root Mean Square (RMS) error of the atrial activity were measured. This method obtained a SNR of 4.4dB±B4ained a S 16µV±V, which is similar to the results reported by Petrenas *et al.*, with a RMS of 20.4µV±7.6.

4. Discussion

The results presented in this work show that the simulated ECG signals are realistic and are giving results in accordance of those reported by previously published state-of-the-art methods of atrial activity extraction.

The results of the RR-interval based AF detector are worse than those reported in the literature. A possible explanation of this phenomenon can be that the generation of random RR intervals was performed with a HMM technique. The State Transition Matrices given in subsection 2.3.2 have been estimated on the MIT-BIH arrhythmia database. Given the nature of this database, there is an under-representation of subjects with normal sinus rhythm. There may therefore be an over-estimation of short and long RR intervals (simulating ventricular ectopic beats), which could be wrongly classified as AF by an RR interval based classifier.

Moreover, the generation of these specific RR intervals could be handled in a different manner. A model of this random firing has been recently proposed [13] and could be used instead of the HMM technique proposed in this work.

It is also worth noting that the final HMM layer was built independently from the state of the previous layer. It is possible to take into account the length of the RR interval for the generation of ectopic beats, as the probability of having a premature ventricular contraction is higher for short RR intervals than for regular or long ones.

5. Conclusion

In this work, we have presented an extension and combination of two previously models for the simulation of ECG signals during paroxysmal AF and added a third model.

This new model will offer the possibility of studying the behaviour of AF classification and atrial activity extraction techniques on examples usually unseen in publicly available databases. Examples such as extremely short AF episodes are usually hard to acquire and therefore they often remain undetected and consequently are not included in large databases. The model presented in this work will also allow for quantitative evaluation of atrial activity extraction methods, since the ground-truth is precisely known..

The model presented here can be generalized for all pathological rhythms and morphologies and in particular the HMM parameters can be adapted to any population.

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