A Hidden Markov Model Approach for Ventricular Fibrillation Detection

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Abstract

Early detection and defibrillation of ventricular fibrillation (VF) has been associated with improved survival of out-of-hospital cardiac arrest (OHCA) patients treated with automated external defibrillators (AEDs). This study proposes a method for VF detection using ECGs obtained from OHCA patients. The dataset of the study contained 596 10-s ECG segments, 144 shockable and 452 non-shockable, from 169 OHCA patients. The dataset was split patient-wise into training (60%) and test (40%) sets. Each ECG segment was band-pass filtered (1-30 Hz), waveform features were computed and fed as observations to a Hidden Markov Model (HMM) that assigned each observation to one of the two hidden states, shockable or non-shockable. The number of possible observations was reduced using k-means clustering. The optimization of the method consisted of feature selection and optimization of the number of clusters through a forward greedy wrapping approach using patient-wise 10-fold cross validation in the training set. The performance of the method was computed in terms of sensitivity (SE) and specificity (SP) using the test set. This procedure was repeated 500 times to estimate the distributions of the performance metrics. The method showed a mean (SD) SE and SP of 94.4% (3.8) and 97.8% (1.2), respectively. The method is compliant with the American Heart Association requirements.

1. Introduction

Out-of-hospital cardiac arrest (OHCA) is one of the leading causes of global mortality with an average incidence between 83.7-95.9 per 100,000 person-years [1, 2]. At the time of collapse most cardiac arrest patients present ventricular fibrillation (VF) [3]. In these cases the recommended treatment is an early electrical defibrillation which might be delivered before ambulance arrival by laypeople using an automated external defibrillator (AED). The shock advice algorithm (SAA) of the AED analyzes the surface electrocardiogram (ECG) and, the AED administers a shock if either VF or ventricular tachycardia (VT) are detected. During the last decades, a vast number of algorithms to detect shockable rhythms [4–8] have been proposed. However, these algorithms have been developed and tested using ECGs from public databases which may substantially differ from those available in OHCA databases. Public databases contain ECGs recorded from Holter devices which enables the analysis of the VF in its first stage, right after its onset. Thus, VF from public databases present higher amplitude and fibrillation frequency than those from OHCA databases which are usually recorded between 5-10 min after the onset, once the AED is on the scene and when VF presents smaller amplitude and lower fibrillation frequency. Non-shockable rhythms in public databases correspond mostly to normal sinus rhythms showing narrow QRS complexes and normal heart rates. While in OHCA databases, these rhythms mainly correspond to asystole (AS) or pulseless electrical activity (PEA) which shows wider QRS complexes and lower heart rates.

The aim of this study is to develop a method to detect shockable rhythms using ECGs obtained from OHCA episodes. To be considered from implementation into AEDs, the method should be compliant with the minimum 90% sensitivity (SE, the capacity to correctly detect shockable rhythms) and 95% specificity (SP, the capacity to correctly detect non-shockable rhythms) requirements of the American Heart Association.

2. Materials and methods

2.1. Data collection

The data used in this study were collected from OHCA patients treated by Tualatin Valley Fire&Rescue (Tigard, OR, USA) using the Philips HeartStart MRx monitor/defibrillator between 2013 and 2014. The dataset of the study consisted of a total of 596 10-s ECG segments, 144 shockable and 452 non-shockable, from 169 OHCA patients. Four emergency medicine doctors annotated by consensus the ECG segments as VF or VT in the shockable category and as organized rhythm (OR) in the non-shockable category. Following the procedure of previous studies in VF detection, AS rhythms were not included as in the SAAs of the AEDs, as AS is usually identified before the shock/no-shock decision using simple algorithms based on thresholds in amplitude or power of the ECG [9, 10]. Figure 1 shows an example of shockable and non-shockable rhythms in the dataset of the study.

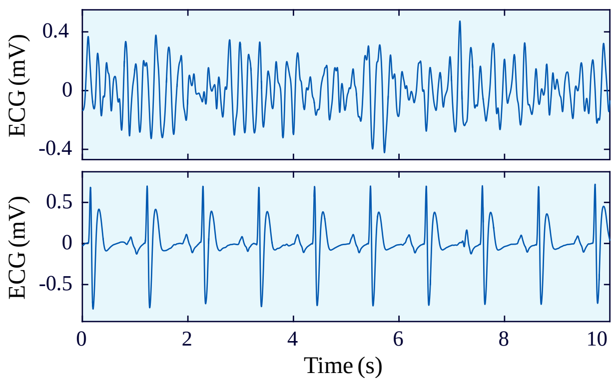

Figure 1. Example of ECG segments of the dataset of the study. The top panel shows a VF and an OR is depicted in the bottom.

2.2. Methods

Preprocessing and feature extraction

The ECG segments were processed following the procedure proposed in Amann et al. [5]. That is, first the mean value of the segment was subtracted, second a five-order moving average filter was applied, then, a high-pass filter with a cutoff frequency of 1 Hz was used to remove the baseline drift and finally, a low-pass Butterworth filter (cutoff frequency of 30 Hz) to eliminate high frequency noise.

From the processed ECG, a total of seven shock/no-shock decision features were computed. These features have been extensively described and showed great discriminative power in previous studies on VF detection [11]. Specifically, the computed features were TCI [5], bCP, bWT [9], x1 and x2 [12] in the time-domain; bW [9] in the frequency-domain; and the complexity feature SampEn [13].

Architecture of the model

Figure 2 shows an overview of the process followed to develop and test the VF detection method. Data were divided patient-wise into two quasi-stratified sets, training (60%) and test (40%), ensuring that the prevalence of shockable rhythms in the test set was between 15-30% (24% in the whole dataset). The selection of the best K-feature subset for the shock/no-shock decision and the optimization of the method were done using patient-wise 10-fold cross validation in the training set. The performance of the method was measured in terms of SE and SP by comparing the shock/no-shock decisions made by the method in the test set against the rhythm annotations made by the clinicians.

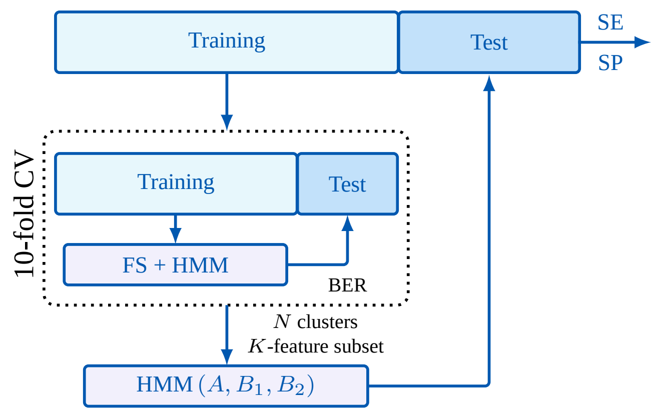

Figure 2. Overview of the procedure followed to develop and test the VF detection algorithm.

VF detection algorithm

The algorithm for the shock/no-shock decision was based on a hidden Markov model (HMM) with a set of two hidden states, $\boldsymbol{Q} = \{q_1, q_2\}$, where q_1 and q_2 represent no-shock and shock decisions, respectively. Figure 3 shows the architecture of the model where $A \in M_{2\text{x}2}$ corresponds to the transition probability matrix where each element, $a_{i,j}$, depicts the probability of transiting from state q_i to state q_j, for $i, j = 1, 2$. $\boldsymbol{O} = \{o_1, o_2, ..., o_N\}$ represents the N different possible observations, and $B_1, B_2 \in M_{\text{Nx1}}$ contain, the so called observation likelihoods or emission probabilities. That is, B_1 includes the $p(o_n|q_1)$ conditional probabilities representing the probability of an observation o_n being generated from the state q_1 (no-shock), and similarly, B_2 contains $p(o_n|q_2)$ representing the probability of an observation o_n being generated from the state q_2 (shock) for $n = 1, ..., N$.

The shock/no-shock decision in the HMM lies in finding the most probable hidden state for the t^{th} analyzed ECG segment, q_i^t, given the observation o_n obtained from that

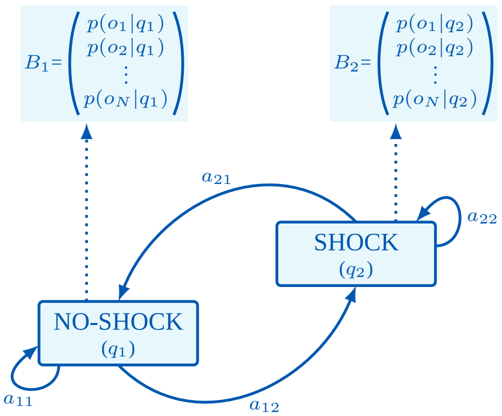

Figure 3. Architecture of the VF detection algorithm based on the HMM with two hidden states q_1 (no-shock) and q_2 (shock).

ECG segment. This decision is based on the following two assumptions:

1. **Markov assumption:** $p(q_i^t|q_i^1...q_i^{t-1}) = p(q_i^t|q_i^{t-1})$ That is, the probability of being at state q_i in the t^{th} analyzed ECG segment only depends on the state of the $(t-1)^{th}$ segment, q_i^{t-1}.
2. **Output independence:** the probability of an observation, o_n, only depends on the state q_i that produced the observation and not on any other states or observations.

Therefore, the shock/no-shock decision function is:

$$q_i^t = \underset{i=1}{\overset{2}{\text{argmax}}}\ p(q_i^t|o_n) \tag{1}$$

where $p(q_i^t|o_n)$ is the conditional probability of being at state q_i in the t^{th} analyzed ECG segment, given the observation o_n, and it is computed as follows:

$$p(q_i^t|o_n) = a_{l,i} \cdot p(o_n|q_i^t) \tag{2}$$

where $l = 1$ when the $(t-1)^{th}$ analyzed ECG segment was classified as non-shockable and $l = 2$ when classified as shockable.

Feature selection and model optimization

As shown in Figure 2, the feature selection (FS) consisted of a forward greedy wrapping approach using patient-wise 10-fold cross validation in the training set. At each step of the feature selection process, the training K-feature vectors were first grouped using k-means into N clusters. Thus, the number of possible observations with which fed the HMM classifier was reduced. Then, using those observations the HMM parameters (A, B_1, B_2) were estimated using the Baum-Welch algorithm [14] through the Statistics and Machine Learning toolbox of Matlab 2015b (MathWorks Inc., MA, USA). Finally, the test K-feature vectors were assigned to one cluster, fed to the trained HMM and classified as shock/no-shock. The decisions were compared against the rhythm annotations made by the clinicians to compute SE and SP.

The criterion for feature inclusion was the minimization of the balanced error rate, BER=1-(SE+SP)/2, of the HMM classifier. The number of selected features was fixed to five, $K = 5$, in order to reduce computational burden and to avoid overfitting while preserving the accuracy in the shock/no-shock classification [11]. Two features, bCP and bWT, that are part of a commercial SAA and have shown great discriminative power in the shock/no-shock decision [9, 11] were always kept in the model and the rest were sequentially added until the best 5-feature subset was obtained. The number of clusters, N, was optimized through a 10x1 grid search in the range $10 \leq N \leq 100$ using the training set.

Evaluation

The best 5-feature subset and the optimal N were used to build the optimal HMM classifier with the whole training set. The performance of the classifier was measured in terms of SE and SP using the test set (see Figure 2). The whole training/test procedure was repeated 500 times in order to statistically characterize the performance metrics.

3. Results

The method showed a mean (standard deviation) SE and SP of 94.4% (3.8) and 97.8% (1.2), respectively. These results are clearly above the performance metrics recommended by the American Heart Association (SE$\leq$ 90% and SP$\leq$ 95%). The method used a median (interquartile range) of 70 (50-90) clusters. The most discriminative features, excluding bCP and bWT that were always included in the model, are ranked in Table 1 according to the number of times (L) each feature was selected in the 500 random repetitions of the training/test procedure.

Table 1. Number of times (L) each feature was included in the model in the 500 random repetitions of the training/test procedure.

Feature	***L***	**Feature**	***L***
bCP	500	x2	278
bWT	500	x1	228
SampEn	487	bW	104
TCI	404		

4. Discussion

This study proposes a method based on a HMM classifier to detect VF during OHCA. Unlike the majority of the previous contributions on VF detection [4–8], our method was developed and tested using ECGs obtained directly from OHCA episodes and met the minimum SE and SP requirements recommended by the American Heart Association. Furthermore, it uses only five-feature subsets which implies low computational demands and makes the method suitable for implementation into AEDs.

The method was build in the basis of two well-known features, bCP and bWT, that compose the core of the SAA of the Reanibex series defibrillators (BexenCardio, Ermua, Spain) and has shown great discriminative power for shock/no-shock decision [9, 11]. Three additional features were added to complete the 5-feature subset used by HMM classifier. The most selected feature was the SampEn which was almost always included in the model (487/500). These results are aligned with those reported by Figuera et al. [11]. This might happen because it adds information on the waveform complexity different from and not correlated with that provided by bCP (slope-based feature) and bWT (time feature). TCI was ranked next (404/500), it is an indirect way to estimate heart rate, and it is well known that higher heart rates are associated with shockable rhythms. The rest of the features complement the previous ones, but there is a great difference in the number of times they were included.

In conclusion, this study have shown that a HMM-based algorithm that uses a 5-feature subset can accurately detect VF during OHCA and might be well suited for implementation into AEDs due to its low computational demands.

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