ORIGINAL ARTICLE

The Classification of Heartbeats from Two-Channel ECG Signals Using Layered Hidden Markov Model

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Abstract

Purpose: Cardiac arrhythmia is one of the most common heart diseases that can have serious consequences. Thus, heartbeat arrhythmias classification is very important to help diagnose and treat. To develop the automatic classification of heartbeats, recent advances in signal processing can be employed. The Hidden Markov Model (HMM) is a powerful statistical tool with the ability to learn different dynamics of the real time-series such as cardiac signals.

Materials and Methods: In this study, a hierarchy of HMMs named Layered HMM (LHMM) was presented to classify heartbeats from the two-channel electrocardiograms. For training in the first layer, the morphology of the heartbeats was used as observations, while observations in the second layer were the inference results of the first layer. The performance of the proposed LHMM was evaluated in classifying three types of heartbeat arrhythmias (Atrial premature beats (A), Escape beats (E), Left bundle branch block beats (L)) using fifteen records of the MIT-BIH arrhythmia database. Furthermore, the obtained results of the proposed model were compared with other HMM generalizations.

Results: The best average accuracy was achieved 97.10±1.63%. The best sensitivity of 96.8±1.24%, 98.85±0.52%, and 95.64±1.41% were obtained for A, E, and L, respectively. Furthermore, the results of the proposed method were better than other HMM generalizations.

Conclusion: Extracting information from time-series dynamics by HMM-based methods has good classification results. The proposed model shows that applying a two-layered HMM can lead to better extraction of information from the observations; therefore, the classification performance of cardiac arrhythmias has been improved using LHMM.

Keywords: Layered Hidden Markov Model; Arrhythmia; Electrocardiogram; Machine Learning; Classification.

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1. Introduction

Today, cardiovascular disease is one of the main causes of death in the world. Cardiac arrhythmia is a very common type of cardiovascular disease, which increases the risk of stroke or sudden cardiac death [1]. Many arrhythmias appear as sequences of heartbeats with abnormal timing or morphology [2]. The most common method for cardiac arrhythmias detection is the use of an Electrocardiogram (ECG) signal, which is widely used as a clinical process [1]. Classification of arrhythmias based on ECG signals is very important in the diagnosis and treatment of various cardiovascular diseases. Over the past years, numerous algorithms have been proposed for the development of automated systems for the accurate classification of ECG signals [3-6]. Most existing researches have mainly focused on the processing of single-lead ECGs [7-9]. However, the ECG signal can be recorded in different locations of the body, and thus multi-lead / channel ECGs can be obtained, which can better reflect the state of the heart and improve the diagnostic function compared to the single-lead ECG [10]. Tanoh *et al.* have used the correlation between the two leads to classify the heartbeats. The results showed higher accuracy of two-lead (95.7%) than single-lead (91%) ECG in classification [11]. Among these leads, lead II emphasizes different segments within the heartbeat, while lead V and its associated leads (V1, V2) are used to classify ventricular arrhythmias [12]. Liu *et al.* have used the extracted features of lead II and V1 to classify five types of arrhythmias by artificial neural networks and in a real scenario, their classification results showed an accuracy of 96.4% [13]. An efficient system for the recognition of three types of arrhythmias was reported by Zadeh *et al.* [14]. They achieved accuracy of 97.14% using twelve two-channel (II, V1) ECG records.

One of the methods used to classify heartbeats is Hidden Markov Model (HMM). HMM is a statistical model and uses a Markov process with a finite number of unobservable or hidden states (a change in the current state depends on the previous state) that generates a sequence of observations [15]. Due to the sequential nature of the events of each cardiac cycle and the quasi-oscillating behavior of the associated signals, the use of HMM can distinguish the underlying structures in the cardiac signals. Previous studies have demonstrated the usefulness of the HMM framework when analyzing ECG signals, and this model was widely used in the detection, classification, and prediction of cardiac abnormalities and arrhythmias such as apnea bradycardia detection in preterm infants [16, 17], ECG segmentation [18, 19], beat detection [20], and heartbeat classification [5, 21, 22]. Recently, Liao *et al.* have developed an automatic heartbeat classification system based on higher-order HMM (HOHMMs) with two leads (II, V1) and obtained an accuracy of 88.33% to classify three types of heartbeats [23].

There are various generalizations of HMM in the literature that have been used in various applications, including classification, to improve performance and overcome certain limitations in the standard HMM. One of these models is the Layered HMM (LHMM), which was first proposed by Oliver *et al.* [24] to recognize human states in a static office environment, and it has been used in various applications such as intension recognition [25-27], event detection, and prediction [28, 29]. Instead of using a huge HMM, LHMM creates a hierarchy of HMMs. There is a set of HMM banks at each layer, related to each dynamic/class. The input of each layer is the output of the previous layer and signals are analyzed in different time resolution, which is defined as “time granularity”. Time granularity indicates the length of a window that segments the sequence of observations. Each layer can be trained and evaluated separately, which decreases the risk of overfitting [15]. The first layer is very sensitive to environmental changes and can be re-trained without training the other hierarchical layers and its inputs are directly analyzed, while the inputs of the following layers are the inferential results of the previous layer [24].

In this study, we intended to introduce the LHMM approach, used in other areas, in heartbeat classification, hence a model based on LHMM was constructed, trained, and evaluated to classify heartbeats using ECG signals from leads MLII and V1. This paper is organized as follows: Section 2, profiles the database that is used in this study. In section 3, the details of the proposed method as well as the optimization and validation methodology are presented. The results obtained are reported in section 4. Finally, the discussion is outlined in section 5.

1.1. Database

To conduct this study, we used the MIT-BIH Arrhythmia Database containing 48 half-hours extracted of two-channel (MLII, V1) ECG recordings. Three types of more or less similar heartbeats (Atrial premature beats (A), Escape beats (E), Left bundle branch block beats (L)) were included for this study. Out of 48 records, 15 records (108, 109, 111, 118, 200, 201, 202, 207, 210, 214, 220, 222, 223, 232, 233) containing all of these types of heartbeats in the MIT-BIH arrhythmia database were selected. Figure 1 shows the morphology of the beats used in this study. Each record of the MIT-BIH arrhythmia database was digitized at a rate of 360 samples per second and independently labeled by two or more cardiologists [30, 31]. The selected records must be preprocessed to use as observation sequences of HMM. The baseline wandering and power line interference noises were removed from the ECG signal by the wavelet denoising approach [32]. QRS complex detection and ECG wave delineation were performed using Pan and Tompkins's algorithm [33] and wavelet transform [34], respectively. Then Trace Segmentation (TS) method was applied to reduce the length of heartbeats. To perform TS, an auxiliary signal was calculated, where each sample corresponds to the sum of the derivatives of the previous samples of the original signal. Thus, an ascending curve was obtained, which started from zero amplitude and ends with amplitude indicating the global change of the signal. Finally, to define sampling points, the range of this curve was divided into as many equal intervals as samples desired [35]. After TS, the length of the observation sequence in every beat was fixed to T=110 samples (minimum length of the beats).

The distribution of arrhythmias between records was not balanced. To have a balanced database in the classification problem, 350 beats were extracted for each type of heartbeats from the aforementioned records.

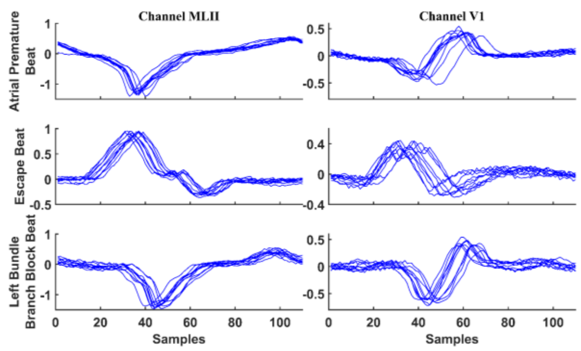

Figure 2. The beats used in this study (10 traces per class). The first and the second columns depict the traces of the MLII and V1 channels for the three types of beats, respectively

2. Materials and Methods

All the analyses were performed in Matlab (2018b, The MathWorks Inc., Natick, MA, USA).

2.1. Proposed LHMM Structure

In this study, a two-layered hierarchy of the HMMs for heartbeat classification was proposed as shown in Figure 2.

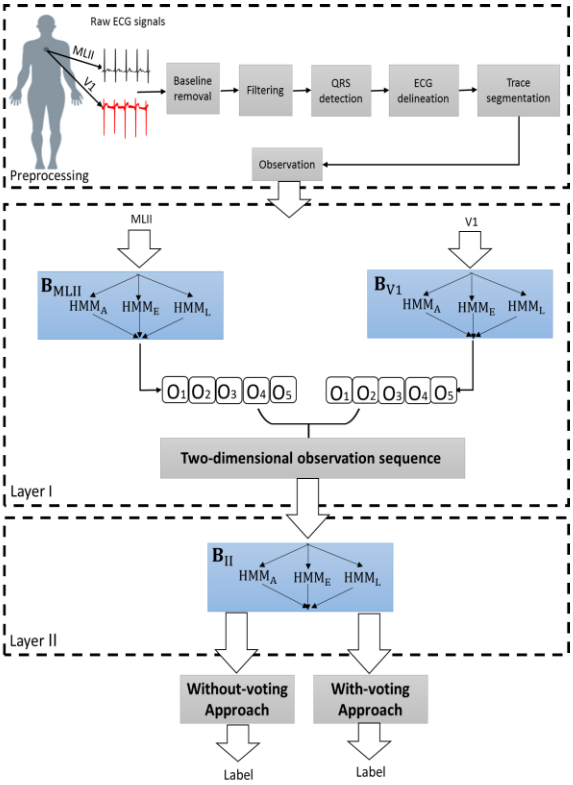

Figure 1. The proposed layered structure for heartbeat classification

The first layer was designed to include two HMM banks to separately analyze V1 (B_{V1}) and MLII (B_{MLII}) for classifying a heartbeat. At each bank, three HMMs were trained, each one for a type of heartbeats (A, E, L) using relevant training data. The input observations of HMMs at the first layer were continuous, and hence to prevent degradation associated with amplitude quantization, Continues Density HMMs (CDHMMs) were built using CDHMM theory [15]. At the first layer, the concept of time granularity was considered as the length of a heartbeat. The extracted heartbeats of two channels (MLII, V1) were separately used as the observations of related HMM banks. In the test step, for the observation O, the HMM of class k, $k \in \{A, E, L\}$, in bank B, $B = B_{MLII}, B_{V1}$, characterized by model parameters set λ_k^B, generates a likelihood value as its output (Equation 1):

$$ll_k^B = logP(O|\lambda_k^B). \quad (1)$$

The likelihood of a dynamic demonstrates the chance of the observation being generated by that dynamic, for which the model by the parameter set of λ_k^B is trained. By comparing the likelihoods generated by the three models inside a bank B, the label of the model with the maximum likelihood was selected. Finally, two sequences were generated from the outputs of HMM banks in the first layer and used as the inputs to the second layer.

The purpose of the second layer is to make the final classification of heartbeats by integrating and analyzing the two outputs of the first layer banks with the time granularity of five heartbeats that were selected empirically. In the second layer, classification was performed by one HMM bank (B_{II}), the inferential results from the first layer (two sequences of discrete labels) were passed to the second layer as observations, and a two-dimensional discrete HMM was trained for each type of heartbeats (three HMMs). The outputs of each bank in the first layer were synchronously segmented with a five-heartbeat length with a stride of one heartbeat and were used as inputs of the second layer. The observation sequence (input) at the second layer was defined by (Equation 2):

$$O(t) = (O_1(t), O_2(t)) \tag{2}$$

Where $O_1(t)$ and $O_2(t)$ represent observation sequences that were obtained from the bank related to MLII and the bank related to V1, respectively. In the second layer, two approaches were considered to determine the label of each heartbeat.

1. Without-voting approach, where the probability of each observation per model was calculated and the label of the model with the maximum likelihood was assigned to the last heartbeat of each observation.

2. With-voting approach, where the probability of each observation per model was calculated and the label of the model with the maximum likelihood was assigned to observation. Finally, the class label of each heartbeat was determined by the maximum voting strategy in five consecutive observations containing the heartbeat.

2.2. The Optimization and Evaluation

The parameters $\lambda_k^B, B \in \{B_{MLII}, B_{V1}, B_{II}\}, k \in \{A, E, L\})$ required for the construction of the proposed LHMM structure were optimally determined. To optimize the parameters and to evaluate the performance of the proposed method in classification, out of 1050 (350 beats per class) extracted heartbeats, 150 heartbeats for each class (A, E, L) were randomly selected for the optimization dataset and the rest for the evaluation dataset.

Out of 150 heartbeats per class in the optimization set, 75 heartbeats per class were randomly selected and divided into two subsets of 50 and 25 heartbeats per class for training and validation in the first layer, respectively. A training phase was applied to estimate the parameters of each HMM using a training observation dataset.

In both banks (B_{MLII}, B_{V1}) of the first layer, three datasets were simultaneously constructed for the training phase. Training datasets were used to train HMMs in relevant banks with the same number of states for all classes. To determine the optimal state of each bank, a set of the number of states, $\{2, 4, \ldots, 9\}$, were investigated and classification performance was evaluated using confusion matrices, by calculating sensitivity (SEN, Equation 3) and accuracy (ACC, Equation 4) on the validation set for each number of states. A confusion matrix was constructed by setting the rows for reference heartbeats and columns for labels obtained by the classification algorithm. To express how successfully the proposed model classified a class over other classes, SEN was calculated. For class k, $k \in \{A, E, L\})$, SEN was defined as follows (Equation 3):

$$SEN_k = \frac{x_{kk}}{\sum_{i=1}^{totall\ classes} x_{ki}} \tag{3}$$

Where $x_{kk}$was the number of heartbeats that have been correctly assigned to the class k whereas $x_{ki}$was the number of heartbeats that were wrongly assigned to other classes by the classification algorithm. ACC was defined as (Equation 4):

$$ACC = \frac{\sum_{i=1}^{totall\ classes} x_{ii}}{\sum_{i=1}^{totall\ classes} \sum_{j=1}^{totall\ classes} x_{ij}} \tag{4}$$

Where x_{ij} was the number of heartbeats annotated as class i but labeled by the detector as class j.

Finally, the number of states of the model with the maximum ACC among the models was chosen as the optimal number of states of each bank. The remaining heartbeats of the optimization set were used to determine the parameters of HMMs in the second layer and were divided into two subsets of 50 and 25 heartbeats per class for training and validation, respectively. To determine optimal parameters in the second layer, three datasets were constructed from the optimization dataset. The five-heartbeat segments for each model (A, E, L) of the second layer were synchronously selected from the outputs of the first layer banks and training data were constructed for both approaches (without-voting, with-voting). The algorithm to obtain the optimal parameters for both approaches was similar to the first one except time granularity was five heartbeats.

Cross-validation was performed on the evaluation set by repeating 5 folds, each of which involved the calculation of metrics. The average and Standard Deviation (STD) of overall folds were reported.

3. Results

The results of the proposed LHMM concerning the problem of heartbeat classification on fifteen records of the MIT-BIH database were reported. The comparison was made concerning existing Markovian models such as HMM with bivariate observations [15], Coupled Hidden Markov Model (CHMM) proposed by Rezek *et al.* [36], and CHMM proposed by Montazeri *et al.* [17].

The optimal values of the number of states in banks of the first and the second layer, as well as calculated metrics in these optimal values, are summarized in Table 1. The SEN and ACC metrics were calculated for various numbers of states to find their optimal values. In the first layer, the maximum training ACC was obtained as 86.64% and 89.75% for banks related to MLII and V1, respectively. In the second layer, the maximum training ACC was obtained as 97.18% for the without-voting approach, and 98.05% for the with-voting approach.

The performance metrics of each bank for two approaches were calculated on test data through cross-validation and reported in Table 2. According to this table, the best results for heartbeat classification were achieved by the second layer in both approaches with an average ACC of 96.14±2.02% for the without-voting approach, and 97.10±1.63% for the with-voting approach.

Table 1. The optimal values of the number of states in the banks of the first layer and the second layer and related metrics

Bank		Class	Optimal Number of States	SEN (%)	Training ACC(%)
1st layer	B_{MLII}	A	4	78.47	86.64
		E	4	98.30	
		L	4	83.16	
	B_{V1}	A	4	80.04	89.75
		E	4	95.21	
		L	4	94.01	
2nd layer	Without-voting approach	A	3	96.10	97.18
		E	3	98.55	
		L	3	96.89	
	With-voting approach	A	3	97.44	98.05
		E	3	98.94	
		L	3	97.78	

Table 2. The cross-validation results of the proposed LHMM at the optimal number of states

Bank	Class	SEN (%)	ACC (%)
B_{MLII}	A	81.82±8. 4	84.70±8.48
	E	94.25±4.69	
	L	78.04±5.9	
B_{V1}	A	77.12±7.48	85.38±7.17
	E	89.96±5.69	
	L	89.07±5.25	
Without-voting approach	A	94.58±1.65	96.14±2.02
	E	98.43±0.48	
	L	95.42±1.65	
With-voting approach	A	96.8±1.24	97.10±1.63
	E	98.85±0.52	
	L	95.64±1.41	

Values are reported as average ± STD

Comparison of the obtained cross-validation results with other Markov-based approaches on test data is reported in Table 3. All results were reported with the optimal number of states. According to this table, the CHMM method proposed by Montazeri *et al.* demonstrates lower STD among the other studied methods. However, the proposed LHMM in both approaches (ACC: 96.14±2.02% for the without-voting approach and ACC: 97.10±1.63% for the with-voting approach) shows a reasonable STD and mostly the best average results in classifying the three classes of heartbeats compared with coupled approaches (ACC: 92.85±4.54% for CHMM proposed by Rezeck *et al.* and ACC: 93.80±1.25% for CHMM proposed by Montazeri *et al*.), and HMM with bivariate observations (ACC: 92.89±5.05%).

4. Discussion

In this study, a classification algorithm based on LHMM was presented to classify three types of heartbeats. We were able to successfully: 1- implement the structure of an LHMM for analyzing ECG of MLII and V1 channels, 2- evaluate the performance of each layer separately, and 3- classify heartbeats with an average ACC of 96.14±2.02% for without-voting approach and 97.10±1.63% for with-voting approach.

LHMMs is an HMM-based hierarchical model that gives the ability for 1- training and evaluating each layer independently, 2- analyzing the observations by different time granularity, and 3- interpreting the effect of each layer separately. Furthermore, the inputs of the second layer in the LHMM structure are processed by the previous one. So, they are less sensitive to noise and baseline fluctuations of the model observations. Finally, classification can be performed using smaller HMMs in the hierarchy structure of LHMM instead of defining a single huge HMM.

The proposed LHMM structure has been trained appropriately without overfitting as indicated by high training and test accuracy of 97.18% and 96.14±2.02% for the without-voting approach, and 98.05% and 97.10±1.63% for the with-voting approach, respectively. Results indicate the robustness of the proposed model in heartbeats classification. For the proposed LHMM, higher accuracies were obtained in the second layer (96.14±2.02% for the without-voting approach and 97.10±1.63% for the with-voting approach) compared to MLII (84.70±8.48%) and V1 (85.38±7.17%) banks in the first layer. These results show that combining the first layer outputs and analyzing them over a longer course of time in the second layer can improve the classification accuracy.

The resemblance among heartbeats in the three classes makes the classification a difficult issue. The sensitivity of heartbeats A, E, L was obtained as 94.58±1.65%, 98.43±0.48%, and 95.42±1.65% for the without-voting

Table 3. Comparison of cross-validation results corresponding to Markovian methods at the optimal number of states

Method	Observation	Class	SEN (%)	ACC (%)
HMM	(MLII,V1)	A E L	90.45±1.98 98.69±0.65 89.52±3.9	92.89±5.05
CHMM proposed by Montazeri *et al.* [17]	(MLII,V1)	A E L	92.74±3.2 95.18±1.45 93.48±2.1	93.80±1.25
CHMM proposed by Rezeck *et al.* [36]	(MLII,V1)	A E L	91.64±1.76 97.87±2.36 89.04±1.17	92.85±4.54
LHMM (Our study) Without-voting	(MLII,V1)	A E L	94.58±1.65 98.43±0.48 95.42±1.65	96.14±2.02
LHMM (Our study) With-voting	(MLII,V1)	A E L	96.8±1.24 98.85±0.52 95.64±1.41	97.10±1.63

Values are reported as average ± STD

approach, respectively, and 96.8±1.24%, 98.85±0.52%, and 95.64±1.41% for the with-voting approach, respectively.

Our proposed LHMM in this study was compared with other Markovian approaches. The obtained results of the proposed LHMM reported higher accuracies (96.14±2.02% for the without-voting approach and 97.10±1.63% for the with-voting approach) than the others (93.80±1.25% for CHMM proposed by Montazeri *et al.*, 92.85±4.54% for CHMM proposed by Rezeck *et al.*, and 92.89±5.05% for HMM with bivariate observations) under the same conditions. In comparison to the previous studies (Table 4), our proposed model in both approaches showed reasonable average accuracies with low STDs.

Although the number of data used in this study might be small, it was reasonable for developing a Hidden Markov-based algorithm. However, the small number of records is considered a limitation of the study and can be addressed by performing the proposed model on different databases and validating more records with different types of heartbeats in the future.

One of the main difficulties of the proposed model is to determine the structure of LHMM (choosing the number of layers and their time granularities) for heartbeat classification. In this study, there were two layers, and time granularities chosen for the first and the second layers were one heartbeat and five heartbeats, respectively. It seems interesting that this step will be done automatically as future work.

The ECG signal is susceptible to various noises and its quality changes with time under different conditions and disappears completely in some cases; therefore, using other cardiovascular signals may be useful to classify the heartbeats [42]. In further works, the LHMM approach could be extended using integrated cardiovascular signal data to improve the classification of heart abnormalities.

5. Conclusion

In this study, a hierarchical structure based on HMM was developed to classify three types of heartbeats. The first layer of the proposed LHMM received two observation sequences from two-channel ECGs in parallel and inferential outputs of the first layer were passed to the second layer as inputs. Two approaches were considered in the second layer.

Based on the obtained results, the first approach (without-voting approach) was able to provide a satisfactory heartbeat classification performance, however, applying voting in the second layer (with-voting approach) further improved the performance of the proposed algorithm in heartbeat classification over 15 records from the MIT-BIH arrhythmia database.

The results showed the capability of the proposed LHMM model to assist the experts in the medical field or to incorporate in the diagnosis system of heart diseases based on ECG signals.

Table 4. Comparison of the classification performance of the proposed method with other approaches

Author	Classifier	#Type of heartbeats	ACC (%)
Liao *et al.* [23]	HOHMM	3	88.33
Zadeh *et al.* [14]	ANN, SVM	3	97.14
Casas *et al.* [37]	LG, ANN, SVM	3	93
Inan *et al.* [38]	ANN	3	96.2
Kumar *et al.* [39]	RFT	3	92.16
Dutta *et al.* [40]	SVM	3	95.82
Lin *et al.* [41]	weighted LD	3	93
This study	LHMM (without-voting approach)	3	96.14±2.02
	LHMM (with-voting approach)	3	97.10±1.63

HOHMM: Higher-Order HMM; ANN: Artificial Neural Network; LD: Linear Discriminants; LG: Logistic Regression; SVM: Support Vector Machines; RFT: Random Forest Classification

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