IEICE TRANS. INF. & SYST., VOL.E95–D, NO.12 DECEMBER 2012

PAPER

Pro-Detection of Atrial Fibrillation Using Mixture of Experts

Mohamed Ezzeldin A. BASHIR†, Kwang Sun RYU†, Unil YUN†, *Nonmembers*, *and* Keun Ho RYU†a), *Member*

SUMMARY A reliable detection of atrial fibrillation (AF) in Electrocardiogram (ECG) monitoring systems is significant for early treatment and health risk reduction. Various ECG mining and analysis studies have addressed a wide variety of clinical and technical issues. However, there is still room for improvement mostly in two areas. First, the morphological descriptors not only between different patients or patient clusters but also within the same patient are potentially changing. As a result, the model constructed using an old training data no longer needs to be adjusted in order to identify new concepts. Second, the number and types of ECG parameters necessary for detecting AF arrhythmia with high quality encounter a massive number of challenges in relation to computational effort and time consumption. We proposed a mixture technique that caters to these limitations. It includes an active learning method in conjunction with an ECG parameter customization technique to achieve a better AF arrhythmia detection in real-time applications. The performance of our proposed technique showed a sensitivity of 95.2%, a specificity of 99.6%, and an overall accuracy of 99.2%.

key words: *atrial fibrillation, cardiac monitoring, electrocardiogram (ECG), training Datase*

1. Introduction

Atrial fibrillation (AF) is one of the most common cardiac arrhythmias. It affects populations over the age of 75 in most cases, and its prevalence decreases with a degreasing in age [1]. AF causes the heart to beat irregularly, leading to an inefficient pumping of blood and changes in blood flow dynamics. These effects can increase the risk of stroke to 15–20% [2]. When AF occurs, the normal electrical signals provided by the sinus node are replaced by rapid circulating waves of irregular electrical signals leading to an uncoordinated atrial activation [3]. These multiple fibrillatory waves randomly circulate across the atrial myocardium and result in a frequently rapid ventricular response. Accordingly, the atrial rhythm is out of synchronization with the ventricular rhythm [4].

An accurate detection of AF is in demand to save people lives. The feasibility of remote monitoring of patients has become clinically important for a better controlling of risks and threads [5].

An electrocardiogram (ECG) provides an essential tool for detecting AF. There are some methods developed to enumerate and detect AF using different features related to ECG parameters. However, there are a massive number of limitations. First the outsized morphological disparity of the ECG is seen not only between different patients or patient clusters but also within the same patient. As a result, the model constructed using an old training data no longer needs to be adjusted in order to identify with new concepts. Second, the number and types of ECG parameters necessary to detect AF arrhythmia with high quality encounter a massive number of challenges in relation to computational efforts and time consumption. Therefore, the current systems cannot detect AF arrhythmia accurately or can detect it late.

We propose a mixture of experts comprising an active learning technique and a technique for adaptive feature selection to accurately detect AF. The former trains the classifier model with updated data, while the latter selects a unique subset of ECG features related to the QRS complex as well as to the P- or T- wave to detect AF arrhythmia. Together, the two methods achieve a sensitive detection with a low computational complexity. Our technique is extended from our previous work that tunes the ECG parameters to detect fifteen arrhythmias [6] and trigger learning [7]. In the rest of this paper, we provide brief descriptions of related work, and the proposed mixture framework. Then, we present experimental work and finally the conclusion.

2. Related Work

2.1 (AF) Detection Techniques

There are some methods developed to quantify and detect AF regarding features related to one of the three main ECG parameters: the absence of P wave, the atrial activity in fluctuating waveforms, and the abnormality of RR intervals [8]. Such algorithms should accurately be able to detect episodes of AF and at the same time have a low computational complexity in order to analyze the ECG signals in real time. Although P wave-based methods show an outstanding performance [9], [10], they have significant limitations. The spectral characteristic of a normal P wave is usually considered to have a low frequency, below 10–15 Hz, which is very small, and it is widely affected by the noise and interfering signals. Thus, the identification of its absence or presence in current real-time applications is a very challenging task. On the other hand, the repetition rate of fibrillation waves, which is considered as the AF frequency, plays an important role in detecting the AF arrhythmia using fibrillatory waveform. This technique is quite inaccurate since there

Manuscript received November 15, 2011.
Manuscript revised April 14, 2012.
†The authors are with School of Electrical & Computer Engineering, Chungbuk National University, Cheongju, 361–763 South Korea.
a) E-mail: khryu@dblab.chungbuk.ac.kr (Corresponding author)
DOI: 10.1587/transinf.E95.D.2982

are many types of arrhythmia fibrillate the ECG waveforms. It can be used in hospitals in conjunction with other direct medical investigation methods; however, in remote monitoring, it is not effectual and useful enough to detect AF. In addition to the described methods, the irregularity analysis of RR intervals has extensively been carried out to detect AF. It known as heart rate variability (HRV) denotes the variations in beat-to-beat rotation at heart beat intervals. Previously, the irregularity of RR intervals (heart beat) has been determined by simple methods that attempt to measure the randomness of RR intervals, such as the calculation of variance among them [11]–[14]. More precise approaches for AF detection commonly build a model to define RR irregularity. Some of these methods involve neural networks [3], the Markov model [15], and logistic regression [16]. Mohebbi and Ghassemian [17] used a support vector machine algorithm to detect AF episodes using the linear and nonlinear features of HRV. RR interval is employed to specify many arrhythmias, such as a normal heart beat, premature ventricular contractions, left and right bundled branch blocks, and paced beats. Therefore, depending only on RR interval to detect AF can cause misleading findings in practical remote real-time applications. Recently, a probability density function method has been proposed by Hong-wei et al. [18]; this method enables one to examine the reconstructed phase space of R-R intervals of a normal sinus rhythm and to study AF. Such method to some extent can reduce the distinguishing RR irregularity of AF from other cardiac arrhythmias. Mostly, all these techniques utilize either the QRS complex mainly the R wave, or the P wave. The literature never shows the employment of other ECG parameters and their intervals to detect AF arrhythmia, although AF affects all the ECG parameters by modifying their shapes and intervals.

In contrast, there are some arrhythmias, though they may have different causes that appear in similar on the ECG. Accordingly, analyzing the QRS, P-wave and other elements of the ECG, and measuring the time interval between these elements are required in real-time AF detection systems. Nevertheless, this is technically not feasible in the current systems because of computation considerations.

2.2 ECG Training Dataset

Confirming local and global datasets is the main two approaches used to learn the classifier model. The Global dataset is built from a large database that most automatic ECG analysis research works refer to [19], [20]. Simply, there are training and testing datasets with different percentages through which the classifier is trained using the training dataset and later predicts the unseen group of data through the testing dataset. One main challenge faced by this technique is the morphologies of the ECG waveforms that widely vary from patient to patient. Accordingly, the classifier learned using the specific data related to an identical patient will perform very well when tested with the unseen data of that patient but often fails when presented with ECG waveforms for other patients. To overcome this problem, the literature shows that there is a trend to learn the classifier via the training dataset as much as possible. This is the commercial trend introduced by ECG device distributers. However, such an approach is criticized in different aspects. First, when using a huge amount of ECG records to build a classifier, development, maintenance, and update will become very complex. Second, it is difficult to learn the classifier using the abnormality ECG obtained during the monitoring process. Therefore, there is a possibility to be unable to detect a specific arrhythmia when applying that model to patient records. Moreover, it is impossible to introduce all ECG waveforms from all expected patients [21].

The local learning set is customized to a specific patient; in other words, it is focused on developing a private learning dataset that corresponds to each patient [22]. It is used to familiarize the classification model with the unique characteristics of each patient. Although this technique appears to alleviate the problem of the learning process, it suffers from a clear problem related to the difficulty in distributing an ECG database because it is time-consuming and labor-intensive. Moreover, few patients are accepted to be involved in the development of the ECG processing method. Thus, there are limitations to the advantages provided by such a technique among the expected audience, even if it is permissible.

Hu et al. [23] overcame this problem through a technique that makes the customization of the training dataset self-organizing by utilizing MOE to realize patient adaptation. This means that there is no need to introduce the manual distribution of the overall database, which minimizes the time and effort consumption. However, such an approach suffers from several pitfalls, such as the lack of sensitivity determined by comparison between two experts (original and patient specific classifiers). Also, it is very costly since the development of a local expert is required for each individual patient to be examined by a professional ECG analyzer. Moreover, it is error-prone awing to its dependability on the type of classifier.

In our previous work, we suggested the use of a nested ensemble technique to solve the problem of the training dataset by manipulating the training dataset for learning the classifier through up-to-date data, and manipulating the ECG features to select the proper adequate set (morphological features) to increase accuracy [24]. However, despite favorable results, synchronizing the two steps was computationally expensive, which precluded a practical implementation. Moreover, the technique was static to some extent.

3. Mixture Model

The proposed mixture model is composed of two main methods, as shown in Fig. 1, namely the active learning and parameter customization methods. These two components work independently, but in a well synchronized manner. ECGs are sent to the active learning system to build

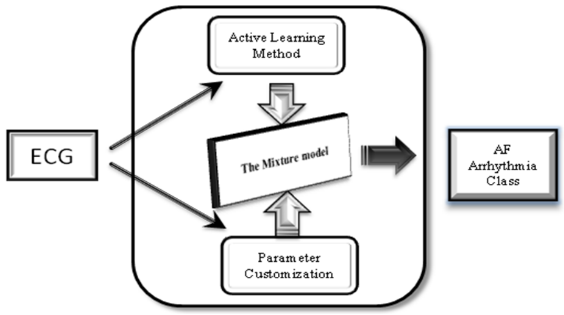

Fig. 1 Flowchart of mixture model.

an updated training model, and also to the parameter customization system to adopt the features of AF arrhythmia. The mixture model integrates these two methods to increase accuracy in real time.

3.1 Active Learning Method

The active learning method was developed to detect AF arrhythmias in a very efficient manner. In essence, it involves the learning of the classifier model with up-to-date training data to reflect changes in morphological descriptors with time. Conventional learning techniques attempt to learn each label assignment process, that is, to study the available features with specific class labels to predict future data. By contrast, active learning is a continuous process that keeps the classifier up-to-date. Partial changes are made to the training dataset when there are insufficient high-quality training data, and complete changes are made when very few high-quality training data are available. That is, new features are introduced to the current training group to update it, or all the present data may be dumped to begin with a fresh dataset if a considerable number of modifications occur. To avoid delay, the technique is based on in-between set of data, which is called cache; thus the change always takes place through the cache. Active learning provides a very high accuracy and reduces the computational cost to some extent since the modifications are not conducted in all situations.

The active learning technique has four steps, as shown in Fig. 2. The initial learning step involves learning from a random set of data without any further considerations. The classifier performance is then evaluated (check) and updated (improve) for consistency. Finally, low-quality data are removed to avoid poor results. The cache is used to substitute the partial or complete modification of the current active training data set. The objective is to minimize hitting the main database as much as possible, so as to save time furthermore increasing the accuracy by double filtering.

3.1.1 Initial Learning Step

First, we start the learning process by utilizing a random group of records (categories), which represent 50% of the overall dataset without considering any factors or any de-

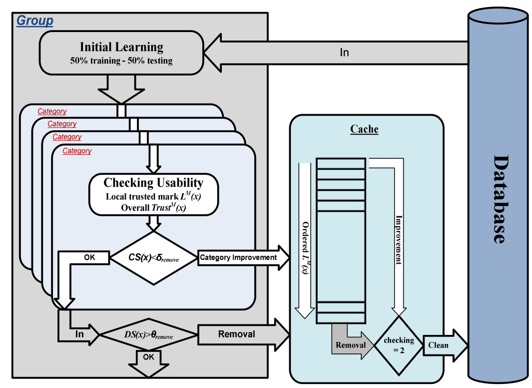

Fig. 2 Active learning process flow.

tails for consideration to start labeling (detecting arrhythmia types). The check and improve steps are later performed to ensure the correctness of the arrhythmia assignment process when applying the classifier model to deal with testing data that represent 50% of the overall dataset.

3.1.2 Checking Usability Step

After the initial learning step, the assigned labels are checked using randomly selected categories (records). This is conducted using the overall trust index $Trust^M(x)$, which is calculated using the local trust index $L^M(x)$ obtained using a label assigned to a specific category with a specific feature vector. If the label of the same category (with the same feature set) is assigned to the target category, the local trust mark $L^M(x)$ will increase. This $L^M(x)$ is calculated as

$$L^M(x) = \sum_{f \in features} \beta_f(F,i).C^s(x) \quad (1)$$

where f is the feature number, F is the contribution of the feature, and $C^S(x)$ represents the score of the category when labeled as arrhythmia (i),which is calculated as

$$C^S(x) = \sum_{f \in features} \beta_f(F,i) \quad (2)$$

The function $\beta_f(F,i)$ checks the set of features (F) in a specific category labeled as arrhythmia (i). It returns "+1" if label (i) is assigned to category (x); otherwise, it returns "−1."

$$\beta_f(F,i) = \begin{cases} +1 & \text{if label(x)} = i \\ -1 & \text{other wise} \end{cases} \quad (3)$$

The local trusted mark $L^M(x)$ dependability is considered on the basis of the overall trusted mark $Trust^M(X)$, which is defined using the sigmoid function Sigmoid $(X)(0.5 < Trust^M(X) < 1)$

$$Trust^M(X) = sigmoid \sum_{x=1}^{n} l^m(x) \quad (4)$$

$$sigmoid(x) = \frac{1}{1+\exp(x)} \quad (5)$$

The overall $Trust^M(X)$ is utilized as a likelihood that indicates the usability of the training set (X). In the case of

$Trust^M(X)$ being greater than some arbitrarily chosen number, (X) is considered to be reliable, i.e., effective; otherwise (X) is considered to be unreliable, i.e., ineffective. The unreliable (X) is either improved or removed. The overall $Trust^M(X)$ fluctuates continuously in relation to the overall performance of the classifier model and its ability to detect AF arrhythmia.

3.1.3 Improvement Step

The checking usability step ends at knowing whether the current training set is reliable or not, depending on different classes assigned to categories. Accordingly, the unreliable set should be modified by a new group of data. This process has two parts: specifying the useless category or categories and replacing it or them with newly selected one(s). In the first part, the category (x) in the active training set (X) is removed if its category score $C^S(x)$ is less than the threshold δ_{remove}. The removal process will be carried out using the following formula:

$$\begin{array}{l}\text{if } C^S(x) < \delta_{remove} \\ \quad \text{then remove}\end{array} \tag{6}$$

The removed category or categories will be sent to the cache not to the main database. Thus the removed categories will be sent to the cache with their $C^S(x)$ in a sending order manner. Accordingly, the saving process in the cache is conducted depending on the category score (the high score at the top). The cache size is fixed so as not to exceed 50% of the total dataset size.

In the second part, a new category is selected randomly from the main database depending on the probability $p^C(x)$ that a specific category (x) will be used in updating the current training set (X). The probability $p^C(x)$ is relative to the overall $Trust^M(X)$ calculated in Eq. (4).

$$p^C(x_{selected/removed}) = \frac{C^S(x_{selected/removed})}{\sum_j C^S(x_j)} \tag{7}$$

We calculate both the P^C value of the substitute category $(x_{selected})$ and the removed category $(x_{removed})$, and then compare them to avoid selecting the removed category. The selected category is newly assigned to the active training group (active X). Then, the process returns to the loop of the check and improve steps.

Starting from the second modification stage, the substitutions take place from the cache not from the main database. The selection of the substituted category depends on $C^S(x)$,thus the category with high score, will be selected i.e., the category on top of the list. This category will be removed from the cache, if selected twice and removed from the active learning set. In this case, it will be replaced with a new category from the main database using Eq. (7) to avoid selecting the same one.

The replacement of the impractical category could be executed several times during the check and update steps. The categories that are removed from the current active training set (X) could be selected in the subsequent update steps for reactivation, which means that all categories could be assigned, regardless of the removal process.

3.1.4 Re-Movement Step

The improvement step is useful when there is a limited number of bad labels using the current group (X),while it is useless when there are multiple defects among the categories, which requires an inherited improvement process consequence. It is very expensive in terms of time, which negatively affects the performance of the classifier model. Therefore, the re-movement step is introduced to deal with this problem.

All categories in (X) are removed, i.e., the active training set is removed if its *defect score* $D^S(X)$ is greater than the threshold θ_{remove}. The removal process will be carried out using the following formula:

$$\begin{array}{l}\text{if } D^S(X) > \theta_{remove} \\ \quad \text{then remove}\end{array} \tag{8}$$

As it happened with the improvement step, the transfer and replacement processes are conducted through the cache except in the first time the initial learning step restarted with the same procedures.

All contents of the cache will be removed, if the cache is reactivated and removed from the active learning set twice. However, a new group of categories (not random) should be selected, which can be achieved using Eq. (7), and the active learning method restarted from the beginning. Note that the ratio of training to validation data is not affected by the improvement or removal step.

3.2 ECG Parameter Customization Method

The aim of parameter customization method is to design a unique feature set that could be employed to describe AF arrhythmia in a very sensitive manner. Customization processes for ECG parameters will take place through one or two parameters plus the *QRS*. In our design, we will achieve a sensitive adaptation with reference to the necessity of the parameters to specifically detect AF arrhythmia classes. Consequently, a considerable accuracy and a low computation complexity will be realized.

Similar arrhythmias often share similar features generated by specific parameters. Therefore, it is useful to predict the parameters required to detect AF arrhythmia. The method uses similar arrhythmias collected from the training data. Parameter involvements are measured using the parameter score *PS* values. The complete parameter list, which shows the AF class labels, is created from the collected similar cases. The parameters (P, QRS, and T) with high *PS* values are grouped together, generating the complete parameter list, which indicates the possibility to assign arrhythmia class (i) to the case with a specific feature set f (distributed through the different parameters included in the complete parameter list). Accordingly, there will be a different parameter list for AF arrhythmia, which increase the

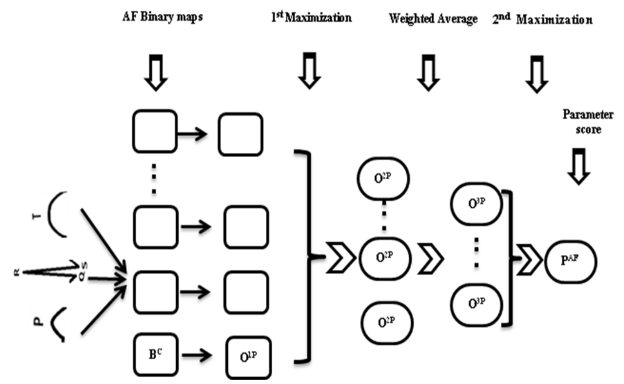

Fig. 3 ECG parameter customization steps.

accuracy, and at the same time, minimize the computation effort. The parameter list for AF arrhythmia is predicted from the parameter list of similar arrhythmias, which are collected from the training data based on general features. The collected cases are used to calculate *PS*. First, the ten most similar arrhythmia cases are collected. Then, the collected cases are manually labeled with binary maps (BMs), which indicate the presence "1" or absence "0" of feature F related to a specific parameter in representing the AF

$$BM_{Arrhythmia}(F) = \begin{cases} 1 & \text{if } F \text{ is positive} \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

Thirty (*BMs*) (ten for each of the parameters P, QRS, and T) are combined together to obtain one general *PS* for AF arrhythmia. As shown in Fig. 3, the general *PS* is obtained through four steps: Gaussian-weighted sum for *BMs*, the first maximization process O^{1P}, Gaussian-weighted averaging O^{2P}, and the second maximization process O^{3P}.

- Step 1: Gaussian-Weighted sum
  Ten binary maps ($BM_p^{'s}$) for each parameter $p \in \{P, QRS, T\}$ are smoothed using the isotropic Gaussian function $g\sigma_{sum}$ for each feature F in the BM_p's

$$O^{1P}(BM_p) = \sum_{f=1}^{n} g\sigma_{sum}[f]BM_p[f] \tag{10}$$

  This will give the sum of the weighted features related to each BM_p, which can be used to detect AF.
- Step 2: First maximization process
  The maximum value of the ten outputs $O^{1P}(BM_p)$ is obtained for every parameter p to detect AF:

$$O^{2P}(p) = MAX_p O^{1P}(BM_p) \tag{11}$$

- Step 3: Gaussian-weighted averaging
  The output O^{2P} is smoothed using the Gaussian function $g\sigma_{avg}$ (p), whose mean is the focused parameter p:

$$O^{3P}(p) = \frac{1}{f}[g\sigma_{avg}(p)O^{2P}(p)] \tag{12}$$

  where $g\sigma_{avg}(p)$ is the standard deviation for each parameter p and f is the number of features used to detect AF. This results in a smooth distribution of scores centered on the focused parameter p.
- Step 4: Second maximization process
  The maximum value of O^{3P} (p) for the three parameters is obtained.

$$O^{4P}(p) = MAX_p O^{3p}(p) \tag{13}$$

As described earlier *PS* indicates the importance of the parameter p in detecting AF. Therefore, we consider the parameter with the highest *PS*, as the main parameter. Then, we calculate the ratio of the other two parameters to the main parameter. If the ratio is more than or equal to 75%, we consider that the other two parameters are also necessary in detecting AF. Consequently, the unique features related to different ECG parameters for describing AF efficiently can be identified.

4. Experimental Work

4.1 Environment

We used a database generated at the University of California, Irvine [25]. The database was obtained from Waikato Environment for Knowledge Analysis (WEKA), containing 279 attributes and 452 instances [26]. The classes from 01 to 15 were distributed to describe normal rhythms, ischemic changes, old Anterior myocardial infarction, old inferior myocardial infarction, sinus tachycardia, sinus bradycardia, ventricular premature contraction (PVC), supraventricular premature contraction, left bundle branch block, right bundle branch block, degree atrioventricular block, degree AV block, left ventricular hypertrophy, atrial fibrillation or flutter, and other types of arrhythmias, respectively. The experiments were conducted in the WEKA 3.6.1 environment, using a PC with processor Intel core (T M) 2 DUO, speed 2.40 GHz and RAM 2 GB. We duplicated the AF and generate a total of 266 instances, including 21 cases of AF with the rest having normal rhythms. The parameters were set as follows. In Eq. (6) $\delta_{remove} = 1.0$, in Eq. (8) $\theta_{remove} = 5.0$. Then we applied the mixture technique with its components using the J48 algorithm.

4.2 Results

4.2.1 Sensitivity, Specificity, and Accuracy Measurements

According to the parameter customization technique, the PS values for P, QRS, and T are 87.9, 94.4, and 68.2, respectively. As a result, AF will be described much better when using the *QRS* complex and *P* waves. Sensitivity, specificity, and accuracy were measured for the detailed performance analysis of the mixture model and its components.

The classification performance is generally presented by a confusion matrix, as shown in Table 1, where TP, TN, FP, and FN stand for true positive (positive predictive value), true negative (negative predictive value), false positive (positive for an unpredicted value), and false negative (negative for an unpredicted value), respectively [27].

Accordingly, we evaluated the accuracy, expressed in percentage of the division of the sum of correctly detected AF (TP+TN) values by the sum of all parameters (TP+TN+ FP+ FN), resulting in a measure of the precision of the algorithm. Sensitivity, expressed in percentage of the division of all true AF (TP) values by the sum of TP + FN values, provides a measure of the capacity of the technique to detect AF. Specificity, expressed in percentage of the division of all non-AF (TN) by the sum of TN + FP values, provides a measure of the capacity of the technique to confirm the absence of AF episodes in the ECG. Table 2 shows the parameters obtained when applying the active learning and parameter customization methods, and the mixture model utilizing the J48 algorithm to detect AF. The results imply that the methods have good predictive abilities and generalization performance. On the basis of the results, the parameter customization method provides a slightly better performance than the active learning methods. In contrast the mixture model achieves an outstanding performance. In particular, the sensitivity and specificity of the proposed mixture model regarding the testing data are 95.2%, 99.6% respectively, and its accuracy is 99.2%.

Several researchers have addressed the AF arrhythmia detection problem using the ECG signals directly or by analyzing the heart rate variability signal [28]–[33]. Table 3 shows the testing results obtained by different methods. It can be observed from this table that the models derived by the active learning and parameter customization methods provide higher accuracy and specificity than those obtained by the other methods reported in the literature, because the active learning method supports the classifier model by updates on the training data, which consider the changes in morphological descriptors, while the other methods use only one set of training data, so the model runs out of domains in presence of morphological changes. In addition, various features are designed by the parameter customization method. The other methods that utilize either P or R waves only result in feature limitations. Also the parameter customization method provides a higher sensitivity than the other methods except that reported in ref. 28. This is due to the large number of AF arrhythmia used. Thus, although the mixture model produces defects in only one case, the sensitivity decreased by 4.8%.

Table 1 Confusion matrix.

		Detected class	
		AF	Normal
Actual class	AF	TP	FN
	Normal	FP	TN

4.2.2 Noise Effects

The performance of the proposed mixture model and its components namely, the active learning and parameter customization methods was further tested in the presence of noisy data. For this purpose, a random noise was applied to the data set in both training and testing duration. The effects of different noise levels were investigated by applying different random noise percentages namely, 1%, greater than 1% and less than or equals 3%, greater than 3% and less than or equals 6%, and greater than 6% and less than or equals 10%. Furthermore, it was applied to ECG parameters namely P, QRS, and T. The measurement accuracy after applying each interval of noise was calculated by obtaining the average. The results obtained in the presence of the noisy data are presented in Fig. 4 to show the performance of the proposed model and its internal components when using the J48 algorithm

The performance characteristics of the three methods with noises are shown in Table 4.

Table 2 Performance of mixture model and its components.

parameters	*TP*	*FN*	*FP*	*TN*	*Sensitivity*	*Specificity*	*Accuracy*
Active learning	17	3	4	242	85.0%	98.4%	97.4%
Parameter customization	18	3	3	242	85.7%	98.8%	97.7%
Mixture model	20	1	1	244	95.2%	99.6%	99.2%

Table 3 Comparative results of different AF detection methods.

Author	*Database*	*Method*	*Sensitivity*	*Specificity*	*Accuracy*
Christov et al. [28]	ECG	P wave	94.7%	-	98.8%
Logan and Healey [29]	HRV	RR irregularity	96.0%	89%	-
Rodriguez and Silveira [30]	HRV	RR interval	91.4%	-	-
Fukunami et al. [31]	ECG	P wave	91.0%	76%	-
Kostka et al. [32]	ECG	Wavelet features	88.0%	85.0	-
Kim et al. [33]	HRV	Time-frequency	-	-	95.2
Mixture model	ECG	QRS +P	95.2%	99.6%	99.2%

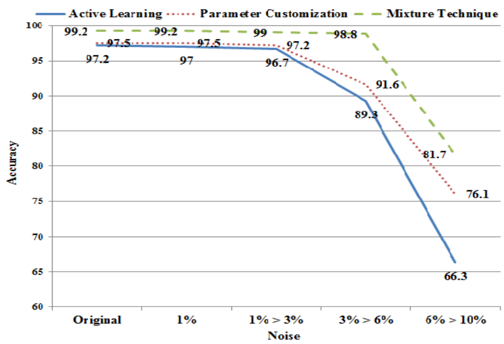

Fig. 4 Accuracy of mixture technique with noises for detecting AF.

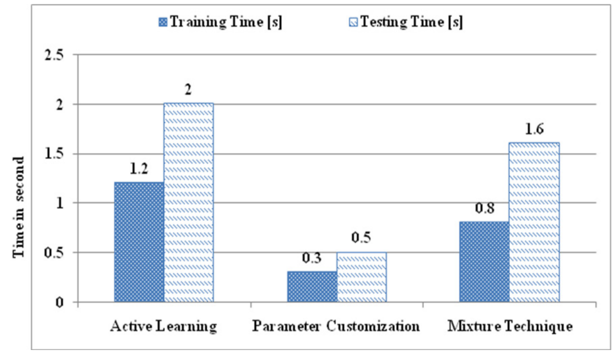

Fig. 5 Speed of mixture technique and its components for detecting AF.

Table 4 performance of mixture technique with noises.

Method	*1%*	*1% > 3%*	*3% > 6%*	*6% > 10%*
Active learning	no	no	Light	Very hard
Parameter customization	no	no	Very light	Hard
Mixture technique	no	no	no	Hard

As can be seen, the active learning method is most sensitive to noise among the methods considered. Its performance achieved within 1% and greater than 1% and less than or equals 3% random noise is very high. Its performance starts to decrease from noise greater than 3% and from noise equals or less than 6%. However, it is significantly affected by noise greater than 6%. In the cases of the parameter customization method and the mixture technique, similar performance characteristics are obtained in all situations with different noise percentages, although the mixture technique outperforms the parameter customization within a noise range greater than 3% and less than or equals 6%.

Generally, the active learning is very sensitive to noise owing to its mechanism of learning, which selects the appropriate group of training data that facilitates the deduction of unknown data. Thus, when finding a group of data that does not match in the overall data, the performance decreases significantly. In the case of the parameter customization the performance is much higher since a limited number of parameters are introduced in the evaluation process.

The performance is accurately much higher with the mixture technique, since it comprises both the active learning and parameter customization methods. The evaluation process occurs in a parallel manner and there is no need for synchronization between the internal components. Therefore, it is very rare to find noises that affect the same features and are evaluated inaccurately way by the two methods.

4.2.3 Time consumption

In this section, we consider the time consumed by the mixture model and its components namely the active learning and parameter customization methods to detect AF.

In Fig. 5, we report the training and testing times of the J48 classifier with the three methods, active learning, parameter customization, and the mixture technique.

As can be seen, parameter customization strategies reduce significantly the computational time for training the classifier, as well as the decreasing testing time. Analogously, using a smaller number of training samples leads to a decrease in time for classifying unknown samples.

However, active learning has the highest computational time among the methods considered, because the process of selecting the right group of data that enhances the detection process is very complex. The mixture technique is affected by the performance of the active learning negatively, simply owing to the time being reduced by the parameter customization method, and then increased by the active learning method.

5. Conclusion

Cardiac health monitoring is challenging data mining and extracting knowledge that has received a great deal of attention over the past few years because of its importance in saving people's lives and reducing risks. Detecting AF arrhythmias through ECG monitoring is a mature research achievement. Wired ECG monitoring in hospitals is very crucial for saving people's lives. However, this type of monitoring is insufficient for detecting the coronary cardiac disease in patients who require continuous follow up.

The contradicting considerations regarding the unique characteristics of patient activities and the inherent requirements of real-time heart monitoring pose challenges for practical implementation. The outsized morphological disparity of the ECG not only between different patients or patient clusters but also within the same patient causes a continuous change. As a result, the model constructed using the old training data no longer needs to be adjusted in order to identify new concepts. In view of that, developing one classifier model to satisfy all patients in different situations using static training datasets is unsuccessful.

Also, analyzing the QRS, P-wave and other elements of the ECG, and measuring the time interval between these elements are required in real time AF detection systems. Nevertheless, this is technically not feasible in current systems because of computation considerations.

In this paper, we present a mixture framework as a proposed solution to the latter problems. The performance of the mixture framework has been evaluated using various approaches. Furthermore, the results demonstrate the effectiveness of our proposed solution. In the future, we plan to perform more experiments to deal with the interrelated ECG parameters.

Acknowledgments

This work was supported by the National Research Foundation of Korea (NRF) grant from the Korea government (Ministry of Education, Science and Technology) (No. 2012-0000478).

References

[1] N.M. Wheeldon, "Atrial fibrillation and anticoagulant therapy," Proc. Euro. Heart J., vol.16, no.10, pp.302–312, 1995.

[2] G. Moody and R.G. Mark, "A new method for detecting atrial fibrillation using R–R intervals," Proc. Comput. Cardiol., vol.10, pp.227–230, 1983.

[3] S. Kara and M. Okandan, "Atrial fibrillation classification with artificial neural networks," Proc. Pattern Recogn, vol.40, no.11, pp.2967–2973, 2007.

[4] F. Chiarugi, M. Varanini, F. Cantini, F. Conforti, and G. Vrouchos, "Noninvasive ECG as a tool for predicting termination of paroxysmal atrial fibrillation," Proc. Trans. Biomed. Eng., vol.54, no.8, pp.1399–1406, 2007.

[5] R.P. Ricci, M. Russo, and M. Santini, "Management of atrial fibrillation — what are the possibilities of early detection with home monitoring?," Proc. Clin. Res. Cardiol., vol.95, no.3, pp.1861–1892, 2006.

[6] M.E.A. Bashir, G. Min Yi, M. Piao, H.S. Shon, and K.H. Ryu, "Fine-tuning ECG parameters technique for precise abnormalities detection," Proc. Int. Conf. Biosci., Biochem., Bioinf., Singapore, pp.305–309, 2011.

[7] M.E.A. Bashir, K.S. Ryu, S.H. Park, D.G. Lee, J.W. Bae, H.S. Shon, K.H. Ryu, E.J. Bae, M. Cho, and C. Yoo, "Superiority Real-Time cardiac arrhythmias detection using trigger learning method," Proc. DEXA Conf. Inf. Tech. Biol. Med. Inform., France, vol.6865, pp.53–65, 2011.

[8] M.E.A. Bashir, D.G. Lee, M. Li, J.W. Bae, H.S. Shon, M.C. Cho, and K.H. Ryu, "Trigger learning and ECG parameter customization for remote cardiac clinical care information system," IEEE Inf. Tech. in Biomed., vol.16, no.4, pp.561–571, 2012.

[9] M. Stridh and L. Sornmo, "Shape characterization of atrial fibrillation using time – frequency analysis," Proc. Comput. Cardiol., vol.29, pp.17–20, 2002.

[10] S. Guidera and J. Steinberg, "The signal-averaged P wave duration: a rapid and noninvasive marker of risk of atrial fibrillation," Proc. Am. Coll. Cardio., vol.21, pp.1645–1651, 1993.

[11] K. Tateno and L. Glass, "A method for detection of atrial fibrillation using R–R intervals," Proc. Comput. Cardiol., vol.27, pp.391–394, 2000.

[12] K. Tateno and L. Glass, "Automatic detection of atrial fibrillation using the coefficient of variation and density histograms of RR and DRR intervals," Proc. Med. Biol. Eng. Comput., vol.39, pp.664–671, 2001.

[13] B. Logan and J. Healey, "Robust detection of atrial fibrillation for a long term telemonitoring system," Proc. Comput. Cardiol., vol.32, pp.619–622, 2005.

[14] I.M. Ishag, A.F.A. Dafa-Alla, G. Min Yi, D.G. Lee, J-W. Bae, and K. Ho Ryu, "Agglomeration, cluster accuracy, hierarchical clustering. On-body sensor," Ad. Exp. Med. Biol., vol.680, no.1, pp.83–88, 2010.

[15] B. Young, D. Brodnick, and R. Spaulding, "A comparative study of a hidden Markov model detector for atrial fibrillation," Proc. IEEE Sig. Proc. Soc. Work. Neu. Net. Sig. Proc. IX, New York, pp.468–476, 1999.

[16] D. Kim, Y. Seo, and C.H. Youn, "Detection of atrial fibrillation episodes using multiple heart rate variability features in different time periods," Proc. 30th IEEE Annual Int. Conf. on Eng. in Med. Biol. Soc., Korea, pp.5482–5485, 2008.

[17] M. Mohebbi and H. Ghassemian, "Detection of atrial fibrillation episodes using SVM," Proc. 30th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., Korea, pp.177–180, 2008.

[18] L. Hong-wei, S. Ying, L. Min, L. Pi–ding, and Z. Zheng, "A probability density function method for detecting atrial fibrillation using R–R intervals," Proc. Med. Eng. Phys., vol.31, pp.116–123, 2009.

[19] G. Bortolan, I. Jekova, and I. Christov, "Comparison of four methods for premature ventricular contractions and normal beats clustering," Proc. Comput. Cardiol., vol.30, pp.921–924, 2005.

[20] L. Peipei, P. Gouchol, K.S. Jung, H.S. Shon, and K.H. Ryu, "QSE: A new 3-D solvent exposure measure for the analysis of protein structure," Proteomics, vol.11, no.9, pp.3793–380, 2011.

[21] G. Clifford, F. Azuaje, and P. McSharrg, "Advanced methods and tools for ECG data analysis," Artech House, 2006.

[22] H. Palreddy and W. Tompkins, "A patient-adaptable ECG beat classifier using a mixture of experts approach," Proc. Trans. Bio. Med. Eng., vol.44, pp.891–900, 1997.

[23] Y.H. Hu, S. Palreddy, and W.J.E. Tompkins, "Patient adaptable ECG beat classification using mixture of experts Approach," Proc. Bio. Eng., vol.44, no.9, pp.891–900, 1997.

[24] M.E.A. Bashir, A. Makki, D.G. Lee, Yi. Min, K.H. Ryu, E.J. Bae, M. Cho, and C. Yoo, "Nested ensemble technique for excellence real time cardiac health monitoring," Proc. World Cong. Comp. Sci. Comp. Eng. Appl. Comput. Conf. (BIOCOMP), Las Vegas, USA, July 2010.

[25] UCI Machine Learning Repository, "Maintain 211 data sets as a service to the machine learning community," http://www.ics.uci.edu/˜mlearn/MLRepository.html, accessed May 5 2009.

[26] WEKA, "is a collection of machine learning algorithms for data mining tasks," http://www.cs.waikato.ac.nz/˜ml/weka/index.html, accessed May 3 2009.

[27] T. Pang-Ning, S. Michael, and K. Vipin, "Introduction to data mining," pp.148–150, 2005.

[28] I. Christov, G. Bortolan, and I. Daskalov, "Sequential analysis for automatic detection of atrial fibrillation and flutter," Proc. Comput. Cardiol, pp.293–296, 2001.

[29] B. Logan and J. Healey, " Robust detection of atrial fibrillation for a long term telemonitoring system," Proc. Comput. Cardiol., vol.32, pp.619–622, 2005.

[30] C.A.R. Rodriguez and M.A.H. Silveira, "Multi-thread implementation of a fuzzy neural network for automatic ECG arrhythmia detection," Proc. Comput. Cardiol., vol.28, pp.297–300, 2001.

[31] M. Fukunami, T. Yamada, M. Ohmori, K. Kumagai, K. Umemoto, K.A. Sakai, N. Kondoh, T. Minamino, and N. Hoki, "Detection of patients at risk for paroxysmal atrial fibrillation during sinus rhythm by P wave-triggered signal-averaged electrocardiogram," Circulation, vol.83, pp.162–169, 1991.

[32] P.S. Kostka and E.J. Tkacz, "Feature extraction for improving the support vector machine biomedical data classifier performance," Inf. Technol. Appl. Biomed., pp.362–365, 2008.

[33] D. Kim, Y. Seo, and C.H. Youn, "Detection of atrial fibrillation episodes using multiple heart rate variability features in different time periods," Proc. Eng. in Med. and Bio. Soc., pp.5482–5485, 2008.

Mohamed Ezzeldin A. Bashir received the Post Graduate Diploma and the M.S. degree in computer science and information technology from Gazera University, WadMadani, Sudan, and the M.S. degree in business administration science from the University of Medical Sciences and Technology, Khartoum State, Sudan. Received the Ph.D. degree in Computer Science from Chungbuk National University, Cheongju, Korea, in 2012. He is a professor in faculty of computer science and information technology, University of Medical Sciences and Technology, Khartoum State, Sudan. His research interests include data mining, information retrieval, database systems, bioinformatics, and biomedicine.

Kwang Sun Ryu received the BSc degree in Information and Communication from Nazarene University, Korea, in 2009. Currently he is a MS candidate in School of Electrical & Computer Engineering, of Chungbuk National University, South Korea. His research interests include data mining, Medical informatics, and Biomedicine.

Unil Yun received the MS degree in Computer Science and Engineering from Korea University, Seoul, Korea, in 1997, and the Ph.D. degree in Computer Science from Texas A&M University, Texas, USA, in 2005. He worked at Multimedia Laboratory, Korea Telecom, from 1997 to 2002. After receiving the Ph.D. degree, he worked as a post-doctoral associate for almost one year at the Computer Science Department of Texas A&M University. After then, he worked as a senior researcher in Electronics and Telecommunications Research Institute (ETRI). Currently, he is an assistant professor in School of Electrical & Computer Engineering, of Chungbuk National University. His research interests include data mining, information retrieval, database systems, artificial intelligence, and digital libraries.

Keun Ho Ryu received the Ph.D. degree from Yonsei University, Korea, in 1988. He is a professor at Chungbuk National University in Korea. He served Korean Army as ROTC. He worked not only at University of Arizona as Post-doc and research scientist but also at Electronics& Telecommunications Research Institute, Korea. He has served on numerous program committees including the IEEE International Conference on Advanced Information Networking and Applications (AINA), the IEEE International Symposium on Mining the Asian Web (MAW), the International Conference on Web Engineering (ICWE), the International Conference on Web-Age Information Management (WAIM), the Asia Pacific Web Conference (APWeb), the International Conference on Web Information Systems (WISE), and he was a demonstration co-chair of the Very Large Data Base Conference (VLDB). His research interests are included in temporal databases, spatiotemporal databases, temporal GIS, ubiquitous computing and stream data processing, knowledgebase information retrieval, database security, data mining, and bioinformatics. He is a member of the IEEE and member of the ACM since 1983