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Robust Detection of Atrial Fibrillation Using Classification of a Linearly-Transformed Window of R-R Intervals Tachogram

MD SAIFUL ISLAM[1], (Member, IEEE), MOHAMED MAHER BEN ISMAIL[1], OUIEM BCHIR[1], MOHAMMED ZAKARIAH[1], AND YOUSEF AJAMI ALOTAIBI[2], (Senior Member, IEEE)

[1]Department of Computer Science, College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia
[2]Department of Computer Engineering, College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia

Corresponding author: Md Saiful Islam (saislam@ksu.edu.sa)

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ABSTRACT Atrial fibrillation (AF) is the most common cardiac arrhythmia. It increases the risk of stroke, dementia, and death; therefore, its timely diagnosis at an initial stage is crucial. Often wearable mobile devices are recommended for the primary detection of this life-threatening arrhythmia. Irregularity of the heartbeat duration, often measured through R-R intervals (RRI), has been intensively investigated during the past four decades for automatic detection of AF. However, little improvement has been made when the input signal (RRI tachogram) contains different types of arrhythmic rhythms. In this paper, we propose a neighborhood component analysis (NCA) based linear transformation of a window of RRI tachogram to improve the robustness of AF detection. Several state-of-the-art classification models are trained and tested using transformed signals, and AF detection performance are evaluated using the challenging MIT-BIH Arrhythmia Database containing various types of arrhythmic rhythms. The experimental results show significant improvement in AF detection performance using the transformed signals compared to those for signals in the original space and after linear-discriminant-analysis-based transformation. In particular, for the Naïve Bayesian classification of the transformed signals, we obtained 98.59% sensitivity, 99.91% specificity, 99.16% positive predictive value, and 99.79% accuracy. The proposed AF detection method outperforms the existing methods reported in the past four decades. Owing to the use of a short window of RRI tachogram (15 consecutive RRIs), the proposed method can be incorporated into a deployable mobile screening device for robust detection of AF.

INDEX TERMS Biomedical signal processing, cardiology, machine learning, medical diagnosis, public healthcare.

I. INTRODUCTION

Atrial fibrillation (AF) is the most common arrhythmia (abnormal heartbeat rhythm) and a major cause of stroke, dementia, and death. The risk for AF increases with age, and almost 9% of people above the age of 65 are suffering from it [1]. Therefore, it is recommended to screen all high-risk people for AF in primary care [2]. Although, the gold standard to detect AF is a 12-lead ECG investigation, such procedure is expensive and time consuming. Timely diagnosis of AF at the initial stage is critical, and wearable devices are also recommended for the primary detection of this arrhythmia [3], [4]. Since AF is often paroxysmal and asymptomatic, frequent screening in an out-of-clinic environment with a readily available and cost-effective device combined with an accurate, real-time, and automatic AF detection algorithm can be more effective for the primary detection of this arrhythmia [5], [6] increasing the chances of survival. Besides, AF episodes could be more effectively detected through daily short-term monitoring with temporally optimized ECG recording using a screening device than day-long Holter monitoring [7], [8]. However, accurate automatic detection is often challenging because subjects (especially at older age) may have different varieties of arrhythmias making the detection process more complicated.

Numerous methods using different types of signals such as the ECG, Plethysmogram [9], [10], and pulse palpation (obtained by an automatic blood pressure monitor) [11]–[13]

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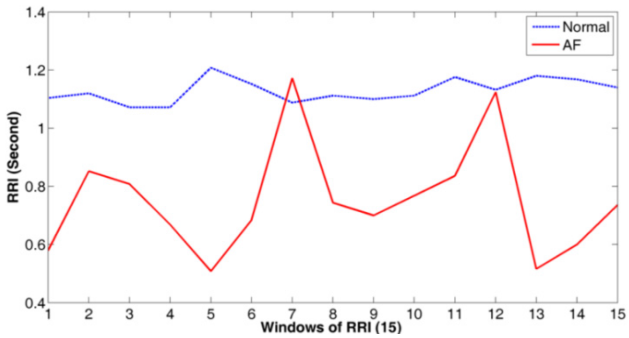

FIGURE 1. Two windows of RRI tachogram for normal and AF rhythm.

signal have been proposed for automatic detection of AF. In particular, the use of ECG signal together with the state-of-the-art machine-learning techniques has been recognized as a feasible approach [14], [15]. However, owing to their high computational cost, these methods can be difficult to deploy into a wearable and mobile screening device. The "irregularity of heartbeat duration," which is a clinically proven characteristic of the AF rhythm, has been primarily investigated for real-time detection of AF [9], [16]–[19]. In fact, R-R intervals (RRI) are the most convenient way to measure the duration of a heartbeat and RRI tachogram can be obtained by using various emerging technologies such as the ECG-based finger probe [20]–[22], Plethysmogram signal based devices (e.g., smartphone) [9], [10], and modified BP monitors [11]–[13]. A new solution based on the accelerometer and gyroscope of smartphones [23] has also been introduced recently to measure the duration of the heartbeat. The AF detection performance using the irregularity of RRI tachogram is also comparable to those of its ECG signal based counterparts [24]. Fig. 1 shows two windows of RRI tachogram for normal and AF rhythms.

Several methods based on the irregularity of RRI for the automatic detection of AF have been proposed. Typically, the detection of AF is formulated as a two-class classification problem when RRI tachogram is used as an input signal. The main detection steps consist of preprocessing, feature extraction, and classification. For preprocessing, different types of filtering [18], [25] and normalization [26], [27] are used. Various types of features are extracted from a RRI tachogram window, such as entropy [9], [25], [28], standard deviation [11, 13], median [29], and RMSSD [9]. For the classification step, researchers mainly use thresholding [17], [18] and machine-learning [19], [30] techniques. Based on the classification task, all AF detection methods could be divided into two broad categories: (i) AF vs NSR (normal sinus rhythm) and (ii) AF vs non-AF classifications. For the AF vs NSR classification, it is assumed that an RRI tachogram window mainly contains any of these two types of rhythms. Most of existing methods fall in this category [24], [29], [31], including methods utilizing machine-learning [30], [32] and deep-learning [19], [33], [34] based classification techniques. Many of these methods have been evaluated with a Physionet database [35], known as MIT Atrial Fibrillation Database (AFDB), containing mostly AF and NSR rhythms. As expected, most of them have reported very high accuracies in detecting AF; such as, 99.19% sensitivity and 99.39% specificity in [24]. Most of these methods ignore the fact that in reality the RRI tachogram obtained from a patient may contain different types of rhythms, which is especially true for older patients. Therefore, a robust method should be able to recognize AF patterns from a signal containing various types of arrhythmias.

One can still define the detection method as a two-class classification problem (AF vs non-AF), where the non-AF class may include NSR and any other types of arrhythmias. In the early 1980s, Moody and Mark [36] attempted the AF vs non-AF classification using the irregularity of RRIs and reported 96.09% sensitivity (Se) and 86.79% positive predictive value (PPV) by evaluating their method on the landmark MIT-BIH Arrhythmia Database (MITDB) [37]. Since then, many threshold-based [16]–[18], [27] and machine-learning-based [19] methods have been proposed and tested for such classification. When these methods were tested with the AFDB, they yielded a very high accuracy; however, this accuracy dropped sharply when they were evaluated with the MITDB. For example, Andersen et al. [19] recently used a combination of deep-learning machines and reported 98.96% sensitivity, 86.04% specificity, and 45.45% PPV when their method was evaluated on the MITDB. Based on the results reported in literature, it can be concluded that, despite the use of various state-of-the-art techniques, a little progress has been made during the past four decades to detect AF.

In this paper, we propose the use of a neighborhood component analysis (NCA) based transformation of an RRI-tachogram window for robust detection of AF from an input signal containing different types of arrhythmic rhythms. The main contribution of this work is that the NCA transformation is able to improve the separation between these two classes in the transformed space. In our proposed method, a window of RRI tachogram is used as input signal, and after transformation, different state-of-the-art machine-learning-based classification models are trained and tested. These models are evaluated using both MITDB and AFDB. Experimental results suggest that the use of this transformation is very effective in the classification of AF vs non-AF problem and outperforms the existing methods by a significant margin.

The rest of the paper is organized as follows. In Section II, we review the literature related to AF vs non-AF classification. We describe the proposed method in Section III and present our experimental results in Section IV. The main findings are discussed in Section V. Finally, Section VI presents the conclusions and future works.

II. RELATED WORKS

In this section, we review the literature closely related to AF detection using RRI tachogram designed to work in the presence of different types of arrhythmias, i.e., the AF vs non-AF classification problem. Specifically, we focus on those works that were evaluated using the challenging MITDB.

We examine their preprocessing techniques, feature extraction methods, and classification models. In addition, measurements of performance obtained by using different window sizes of RRI tachogram are summarized.

Preprocessing is often considered as an important initial step for many AF detection methods and different types of preprocessing techniques have been investigated. Particularly, ectopic beats have been considered as a common noise [9], [18], [28], [38] for input signal (RRI tachogram), and the median filter have been used to remove these beats. Moody and Mark [36] used a first-order filter for noise removal and an interpolation technique to cancel the quantization error. Islam et al. [27] normalized the heartbeat duration to discard the effect of shorter heartbeat durations of the AF rhythm before measuring the irregularity of different rhythms.

Entropy has been used as the most common measure of the irregularity of an RRI window. Different varieties of entropy, such as the Shannon entropy [25], [28], [38], alphabet entropy [16], normalized entropy [27], have been adopted as a feature extraction technique. Specifically, entropy has been measured using a window of RRIs or a symbolic dynamic representation of it [16], [17], [25]. Petrėnas et al. [18] used a normalized Heaviside step function based on the principle of sample entropy estimation [18]. Lee et al. [38] used the variance of time-varying coherence functions combined with the Shannon entropy. Lian et al. [39] created a scatterplot of RRI versus change of consecutive RRIs and divided it into 2D grids with a 25-ms resolution into two axes and the number of nonempty cells were used as a measure of irregularity.

Measurement of the irregularity (e.g., entropy) turns the RRI tachogram window into a scalar. Next, the classification task is typically performed by thresholding. Different methods used different window sizes and reported different sets of performance when evaluated with the MITDB [28]. Dash et al. [28] determined the optimal length of the window (128 RRIs) and threshold values, and attained 90.02% sensitivity and 91.2% specificity with their method. Lian et al. [39] tested their method with different window sizes, such as 32, 64, and 128. The best performance (98.9% sensitivity, 78.8% specificity) was obtained using the largest window. Zhou et al. [17] proposed the thresholding of the Shannon entropy computed through a symbolic dynamic representation of RRIs window. Using a window of 127 RRIs, this approach resulted in 97.83% sensitivity, 87.41% specificity, 47.67% PPV, and 88.51% accuracy. Lee et al. [38] performed thresholding of the variance of time-varying coherence functions combined with the Shannon entropy. They tested their method using two different window sizes: for 128 RRIs, their approach attained 91.1% sensitivity and 89.7% specificity; for 12 RRIs, their method yielded 91.4% sensitivity and 84.1% specificity. Petrėnas et al. [18] used a shorter window size of 8 RRIs and obtained 97.8% sensitivity and 86.4% specificity.

Several other studies used a window of RRI tachogram as a multidimensional feature vector to be classified using machine-learning techniques. Moody and Mark [36] used the first-order Markov process model for a window of 20 RRIs to classify it as an AF or non-AF sequence. They used 12 records from the MITDB as a training set and reported 96.09% sensitivity and 86.79% PPV. Andersen et al. [19] used an ensemble of deep-learning machines such as convolutional (CNN) and recurrent (RNN) neural networks for detecting AF by using a window of RRI tachogram of size 30. Although high performance on the AFDB dataset was achieved, the performance was reduced significantly when tested with the MITDB (sensitivity 98.96% and specificity 86.04%). There are a few methods that extract several features from the same window and use different types of machine-learning techniques for classification [23], [30].

To summarize this section, it could be noted that most of the reported works focusing on solving the AF vs non-AF classification are based on feature extraction (usually a scalar) from a window of RRI tachogram and subsequent classification using a predetermined threshold. The use of advanced machine-learning techniques for such a classification problem has received attention only recently. One important concern about the existing approaches is the window size of RRI tachogram. Most of the methods yield better performance with larger window sizes. Based on the reported performance of these methods on the MITDB, it may be noted that only a little improvement has been made after four decades of research on the detection of AF.

III. METHOD

The heart of a human produces a semi-periodic rhythm of heartbeats, and each heartbeat is initiated by an electric impulse from the sino-atrial (SA) node. During NSR, each heartbeat consists of a sequence of waves such a P wave, QRS complex, and T wave. However, the variation in the heartbeat interval, known as heart rate variability (HRV) is a physiological phenomenon of a healthy heart and is caused by sympathetic, parasympathetic, and respiratory activities [40]. The heartbeat duration may also vary in several arrhythmic rhythms such as AF, and bigeminy [16]. Fig. 2 shows RRI tachograms (an RRI is marked by a double-sided arrow) of such rhythms on sample ECG signals.

It could be observed form figure 2(a) that during NSR the variation of RRI is relatively small whereas during ventricular bigeminy (VBI), as shown in figure 2(c), the variation rather follows a regular pattern of alternative short and long RRIs. However, during AF rhythm, the variation in RRI is markedly different from other rhythms and such variation is often characterized as ‘‘irregularly-irregular,’’ as can be observed in Fig. 2(b). In this case, the electrical impulses are originated from different parts in the atria, rather than from the usual SA node, and spread throughout the atria in a rapid and disorganized way. Only some of these impulses get through the atrioventricular (AV) node and produce a highly irregular ventricular rate. Therefore, if we measure the heartbeat duration through consecutive ventricular waves (e.g., R-peaks on the ECG signal), we obtain an

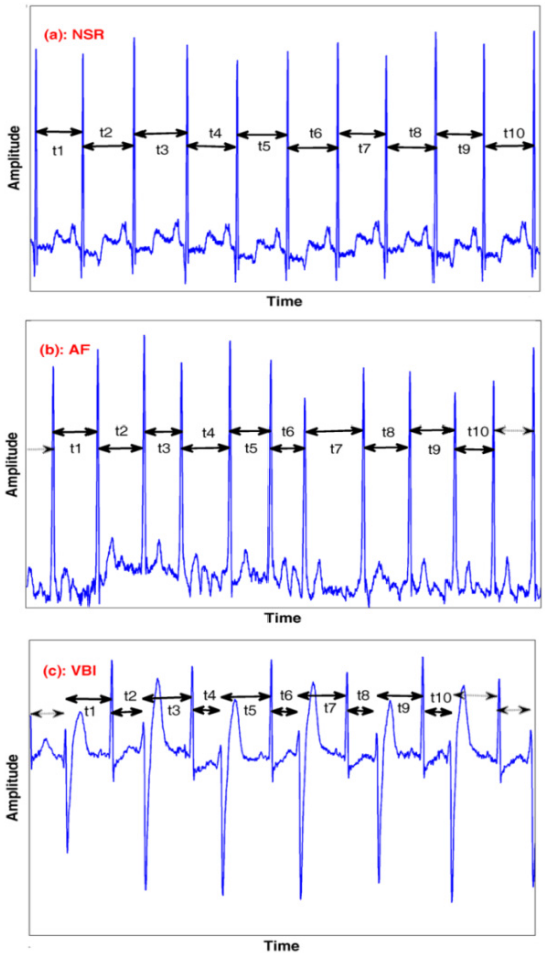

FIGURE 2. RRI tachograms, showing duration (t_i) between two consecutive R-peaks on an ECG signal, illustrates RRI variation during three different rhythms: (a) NSR, (b) AF, and (c) VBI.

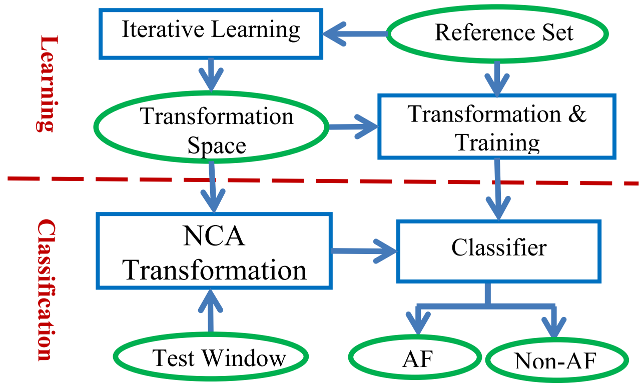

FIGURE 3. Block diagram of AF detection method using NCA transformation of RRI tachogram.

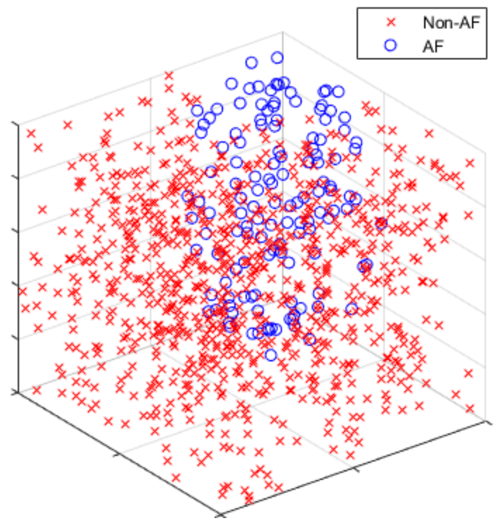

FIGURE 4. Reference set of 3D RRI tachograms in original spaces.

irregularly-irregular heartbeat rhythm. This irregularity is the most important clinical characteristic to identify a patient with AF.

As outlined is Section II, most of the existing automatic detection methods measure the irregularity of a window of RRIs by a metric, such as entropy, and perform thresholding for classification. In this work, we use a short window of RRI tachogram as the input signal and preprocess it to remove ectopic beats and other outliers. Ectopic heartbeats may be yielded by premature atrial or ventricular contractions and in most of the cases RRI becomes significantly larger than that of a normal heartbeat. We have used a median filter which has been found effective to remove these ectopic beats [18].

The preprocessed signal is transformed to NCA space, and classification is performed in the transformed space as illustrated in Fig. 3. The optimal transformation space is determined by an iterative learning process, as discussed in Subsection A of this section. In Subsection B, we discuss the detection of AF as a two-class classification problem. In Subsection C, we analyze the computational efficiency of the proposed method and its feasibility to be deployed into a wearable screening device.

A. NCA TRANSFORMATION

A window of RRI tachogram containing d complete heartbeats of durations $t_1, t_2, \ldots, t_d$ can be represented by a vector in $\Re^d$ as follows:

$$\mathbf{x} = [t_1, t_2, \ldots, t_d]^T. \tag{1}$$

Although several recent methods have utilized a window of RRI tachogram as a multidimensional feature vector [19], [31], [34], they have failed to achieve the desirable performance for the AF vs non-AF classification. This can be attributed to the complex nonlinear decision boundaries in higher dimensional space. Fig. 4 shows the nonlinear separability of a reference set of 3D RRI tachograms in its original space. Hence, the transformation of a vector is a natural choice to enhance the separability of these two classes.

The linear discriminant analysis (LDA)-based transformation, which minimizes intra-class variability and maximizes inter-class variability at the same time [41], seems like a promising alternative. To investigate the efficiency of such LDA-based transformation, we used the same set of reference windows (vectors) and transformed them into the new space

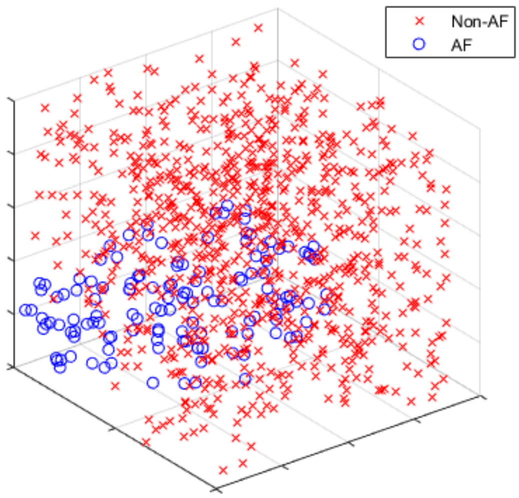

FIGURE 5. Effect of LDA transformation, applied on the same reference set of 3D RRI tachograms as in Fig. 4, shown in the transformed space.

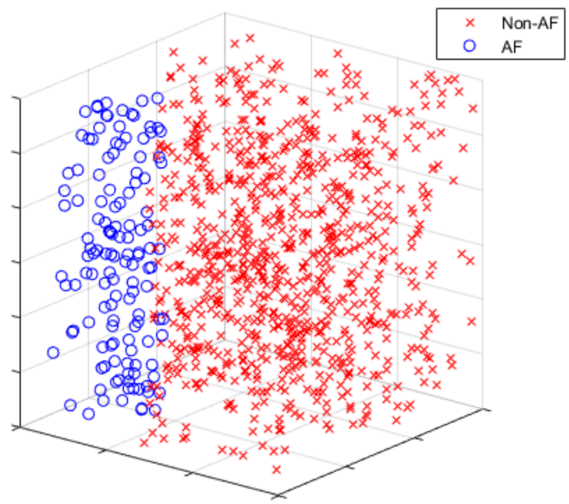

FIGURE 6. Effect of NCA transformation, applied on the same set of reference 3D RRI tachograms as in Fig. 4, shown in the transformed space.

without dimensionality reduction, as shown in Fig. 5. Furthermore, in Section IV, we report the results obtained using different classification models for a set of transformed signals with larger dimensionality and it could observe that the LDA transformation offers little improvement in the performance of AF detection.

In this paper, we investigated NCA transformation to maximize the separation between these two classes in the transformed space. Suppose, we have a set of n reference (training) samples $\{(\mathbf{x}_i, c_i)\}$, $c_i \in \{\text{AF, non-AF}\}$, $i = 1 \ldots n$. The NCA transformation of a feature vector $\mathbf{x}_i$ is a linear transformation defined as

$$\mathbf{y}_i = A\mathbf{x}_i \tag{2}$$

where $\mathbf{y}_i \in \Re^d$ and A is the transformation matrix.

To determine the optimized transformation coefficient matrix, we maximize the probability of the reference vectors from the same class to be relocated in the same neighborhood in the transformed space. A similar technique, known as neighborhood component analysis, has been previously investigated for feature selection [42] and dimensionality reduction [43]. Because the features are not correlated, we restrict A to be a diagonal matrix as in [42].

$$A = diag(w_1, w_2, \ldots, w_d) \tag{3}$$

In the transformed space, each data instance $\mathbf{y}_i = A\mathbf{x}_i$ is associated with a different data instance $\mathbf{y}_j = A\mathbf{x}_j$ as its neighbor (using the Euclidean distance) with the probability p_{ij}:

$$p_{ij} = \begin{cases} \dfrac{e^{-\mathbf{w}^T(\mathbf{x}_i - \mathbf{x}_j)}}{\sum_{k \neq i} e^{-\mathbf{w}^T(\mathbf{x}_i - \mathbf{x}_k)}} & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases} \tag{4}$$

where $\mathbf{w} = [w_1, w_2, \ldots, w_d]^T$ is a vector consisting of the diagonal elements of A.

Since, our objective is to maximize the separation of the two classes in the transformed space, we compute the average probability p_i of a given vector $\mathbf{y}_i$ to be the neighbor of all vectors belonging to the same class as c_i in the transformed space:

$$p_i = \sum_{j=1}^{n} z_{ij} p_{ij} \tag{5}$$

where z_{ij} depends on the class labels $c_i, c_j \in \{\text{AF, non-AF}\}$ of two concerned reference samples $\mathbf{x}_i$, $\mathbf{x}_j$ respectively:

$$z_{ij} = \begin{cases} 1 & \text{if } c_i = c_j \\ 0 & \text{otherwise} \end{cases}. \tag{6}$$

The objective we maximize is the average probability of all vectors to be the neighbor of samples from the same class:

$$J(\mathbf{w}) = \sum_{i=1}^{n} p_i. \tag{7}$$

The determination of vector $\mathbf{w}$ is then expressed as per the following optimization problem:

$$\hat{\mathbf{w}} = \underset{w}{\text{argmax}}\, J(\mathbf{w}) \tag{8}$$

An iterative algorithm is used to update $\hat{\mathbf{w}}$ by using an appropriate regularization term to avoid local optima as in [42]. Fig. 6 shows the transformed reference set after the proposed transformation where $\hat{\mathbf{w}}$ was estimated using the iterative algorithm. It could be observed that the distribution of the reference vectors has been changed, and the two classes become more separable in the transformed space.

B. AF DETECTION

After applying the transformation to reference vectors, we obtain transformed reference set $\{\mathbf{y}_i, c_i\}$, which is used as the training set. A wide variety of classification models exists. We have selected some state-of-the-art machine learning-based models such as nearest neighbor (NN), Naïve Bayesian (NB), support vector machine (SVM), artificial neural network (ANN), and deep-learning machine (DLM) for the detection of AF as a two-class classification problem. The transformed reference vectors are used to train these machines, and the classification is performed on a set of test vectors.

We selected the Naïve Bayesian method for the two-class classification problem as a simple method for AF detection. Suppose $\mathbf{m}$ is the mean of transformed vectors belonging to the AF class in the NCA space:

$$\mathbf{m} = \sum_{i=1}^{n} z_i \mathbf{y}_i \tag{9}$$

where z_i depends on the class label c_i for the concerned reference sample $\mathbf{x}_i$:

$$z_i = \begin{cases} 1 & if\ c_i = AF \\ 0 & otherwise \end{cases}. \tag{10}$$

Now, by using the Naïve Bayesian assumption that the two classes follow two Gaussian distributions, discrimination functions $g(\mathbf{x}|\ \hat{\mathbf{w}})$ for a test vector $\mathbf{x}$ in the transformed space can be obtained using estimated values $\hat{\mathbf{w}}$ and $\hat{A}$ using Eq. (8) as follows:

$$g(\mathbf{x}|\hat{\mathbf{w}}) = (\mathbf{m})^T \hat{A}\mathbf{x} - \frac{1}{2}||\mathbf{m}||^2. \tag{11}$$

Test vector $\mathbf{x}$ is detected as AF if $g(\mathbf{x}|\ \hat{\mathbf{w}}) > 0.5$.

C. COMPUTATIONAL EFFICIENCY

Computational efficiency of an AF-detection method is an important issue when it comes to implementing and incorporating the method into a wearable-mobile screen device. Although the determination of transformation vector $\hat{\mathbf{w}}$ is an iterative method, it can be performed offline using a set of reference vectors. Similarly, the mean vector $\mathbf{m}$ for the AF class can be obtained in this phase. The actual classification becomes a non-iterative method and requires test vector $\mathbf{x}$ to be transformed into the NCA space to compute the discriminant function in (11), which can be rewritten as

$$g(\mathbf{x}) = \sum_{i=1}^{d} m_i \hat{w}_i x_i - \frac{1}{2}\sum_{i=1}^{d} m_i^2 \tag{12}$$

Because the size of an RRI tachogram window (d) is small and constant, the discriminant function can be computed quite efficiently to be implemented in any mobile computing device requiring minimal computing power.

IV. EXPERIMENTS

We implemented the iterative algorithm to determine transformation coefficient matrix, trained the Naïve Bayesian classifier using transformed reference vectors, classified a set of test vectors, and tested the classification performance using two publicly available and landmark databases. To compare the effectiveness of the NCA transformation, we also applied the same classification protocol on the same training and test set before any transformation of reference vectors and transformed reference vectors using LDA-based transformation. In addition to the Naïve Bayesian classification, we used several other classification models such as the NN, SVM, ANN, and DLM to test the effectiveness of the proposed transformation on these classification models as well.

A. DATABASES AND PREPROCESSING

In this paper, we used short windows of RRI tachogram, obtained from ECG signals provided by MITDB and AFDB, to assess the performance of the proposed AF detection method. In both databases, the locations of R peaks on ECG records and the rhythm annotation of each beat are marked. We used all 48 ECG records of MITDB in which the sampling rate is 360 samples/s. As mentioned before, this database is challenging because it includes records with various rhythms. In particular, it contains 11,670 heartbeats labeled as AF out of a total of 112,598 heartbeats. AFDB contains a set of 25 ECG records of 10 h each, which were sampled at 250 samples/s. The ECG signals in this database include mostly NSR and AF rhythms. In particular, 521,417 heartbeats out of 1,223,145 heartbeats are labeled as AF.

An RRI tachogram signal was obtained for each ECG record by computing the duration between consecutive R-peaks. Next, a median filter of size $m = 2l+1$ was applied using a sliding window to replace the center of the window (t_i) with the median to remove ectopic beats and outliers [18] as follows:

$$t_i = \text{median}(t_{i-l}, \ldots, t_i, \ldots, t_{i+l}). \tag{13}$$

After filtering, we divided a record into windows of d consecutive RRIs. It should be noted that a window may contain only AF beats, only non-AF beats, or a mix of both. The objective here is to classify the whole window as AF or non-AF. We converted the original beat-to-beat annotations of a window such that the whole window was assigned a ground truth: AF annotation was assigned only if the number of true AF beats (as annotated in the database) exceeded a minimum percentage threshold [28], [44], otherwise it was annotated as non-AF. We denoted this minimum percentage threshold as p.

B. CROSS-VALIDATION AND EVALUATION

We used ten-fold cross-validation to train and test several classification models in our experiments. At each round, all windows of RRI tachogram obtained from a database were divided into training and test sets. The training set was used as the reference set for the iterative learning process to compute $\hat{\mathbf{w}}$ which consists of the parameters of transformation as described in Section III.A. We tested two variants of the iterative process such as the stochastic gradient descent (SGD) and limited memory Broyden-Fletcher-Goldfarb-Shanno (LBFGS) [45] algorithms with random and constant (one) initial values for the optimization. It was observed that the use of LBFGS and random initial values yielded the best overall performance.

After obtaining transformation parameters $\hat{\mathbf{w}}$, the training and test sets were transformed into the new space.

TABLE 1. Effect of median filter size, used for noise removal from a RRI tachogram, on classification: These results were obtained from MITDB by using Naïve Bayesian classification of transformed signals with $D = 15$, $P = 80\%$.

Median filter size (m)	Se (%)	Sp (%)	PPV (%)	ACC (%)
No filtering	37.87	97.92	66.45	92.26
3	77.26	99.10	90.19	97.04
5	88.84	99.69	96.84	98.67
7	95.76	99.82	98.27	99.44
9	96.47	99.97	99.71	99.64
11	98.59	99.91	99.16	99.79

TABLE 2. Effect of window size on classification: These results were obtained from MITDB by using Naïve Bayesian classification of transformed signals with $M = 11$, $P = 80\%$.

Window size (d)	Se (%)	Sp (%)	PPV (%)	ACC (%)
6	40.70	99.18	83.33	93.82
8	55.36	99.38	88.57	95.88
10	69.23	99.21	91.01	96.09
12	73.81	98.95	87.32	96.70
15	98.59	99.91	99.16	99.79

The transformed training set was used to train a classification model, whereas the transformed test set was used to test the trained model. After the classification of a set of test windows of RRI tachogram, we obtained true positive (TP), false positive (FP), true negative (TN), and false negative (FN) classifications. Next, we computed the sensitivity ($Se = TP/(TP+FN)$), specificity ($Sp = TN/(TN+FP)$), positive predictive value ($PPV = TP/(TP+FP)$), and accuracy ($ACC = (TP+TN)/TP+TN+FP+FN)$) of AF detection. We computed and reported the average classification performance over all rounds of cross-validation for each database separately.

C. RESULTS

At first, we tested the sensitivities of different parameters such as median filter size (m), window size (d) of the RRI tachogram, and percentage threshold (p) to the performance of the Naïve Bayesian classifier using the MITDB. We applied a median filter to the RRI tachogram with increased sizes such as 3, 5, 7, 9, and 11. Table 1 shows the classification performance for different filter sizes. We also tested the classification performance without filtering.

The window size is an important parameter, and we tested only short window sizes of RRI tachogram for efficient AF detection. We evaluated our method for different window sizes (d) such as 6, 8, 10, 12, and 15 RRIs. Table 2 shows effect of the window size on the classification performance.

Percentage threshold (p) for the annotation of window was varied from 50% to 100% with incremental steps of 10%. Table 3 shows the effect of different values of p for window size $d = 15$, median filter size $m = 11$ and evaluated with MITDB.

We tested the effect of classification performance of the proposed transformation on different machine-learning-based classification models. Different state-of-the-art machine-learning-based classification models (as shown in Table 4) were implemented, trained with the same training set, and tested with the same test set. We tested the performance of classification without any transformation (original space), LDA-based linear transformation (LDA space), and proposed NCA transformation (NCA space) using different classification models as shown by Table 5.

We also tested the performance of the proposed transformation on AFDB. Table 6 summarizes the obtained performance for both datasets using the Naïve Bayesian classifier

TABLE 3. Effect of percentage threshold on classification: These results were obtained from MITDB by using Naïve Bayesian classification of transformed signals with $M = 11$, $D = 15$.

Percentage threshold (p)	Se (%)	Sp (%)	PPV (%)	ACC (%)
50%	97.39	99.96	99.58	99.71
60%	98.05	99.91	99.16	99.73
70%	98.33	99.93	99.31	99.77
80%	98.59	99.91	99.16	99.79
90%	98.14	99.96	99.56	99.79
100%	98.86	99.94	99.43	99.84

TABLE 4. Different models with architectures/parameters used for classification.

Classification model	Architecture/Parameter
Nearest neighbor (NN)	Nearest neighbor search method: "*kdtree*" Distance measure: "Euclidean"
Naïve Bayesian (NB)	Data distribution: "Normal"
Support vector machine (SVM)	Kernel function: "Linear" Optimization routine: *L1* soft-margin minimization by quadratic programming
Artificial neural network (ANN)	**Feedforward network:** Size of the row vector of the hidden layer: 10 Performance function: "crossentropy" Training function: scaled conjugate gradient backpropagation
Deep learning machine (DLM)	**Long short-term memory network**: A bidirectional LSTM with 100 hidden units The fully connected layer of size 2 A softmax layer and a classification layer

TABLE 5. Effect of NCA transformations on different classification models: These results were obtained from MITDB by using $M = 11$, $D = 15$, $P = 80\%$.

Space		NN	NB	SVM	ANN	DLM
Original	Se (%)	80.20	18.00	31.00	24.53	16.56
	Sp (%)	99.03	88.52	91.66	98.26	98.55
	PPV (%)	90.00	14.52	28.70	61.90	55.56
	ACC (%)	97.17	81.62	85.73	90.62	90.49
LDA	Se (%)	72.00	44.00	51.00	29.66	17.75
	Sp (%)	97.51	92.63	62.95	97.84	98.61
	PPV (%)	75.79	39.29	12.98	58.90	61.22
	ACC (%)	95.01	87.88	61.78	91.40	89.71
NCA	Se (%)	95.06	98.59	97.00	92.00	78.00
	Sp (%)	99.56	99.91	99.89	99.67	98.27
	PPV (%)	95.77	99.16	98.98	96.84	82.98
	ACC (%)	99.13	99.79	99.61	98.92	96.29

TABLE 6. Classification performance for AFDB and MITDB: These results were obtained by using Naïve Bayesian classification of transformed features with $M = 11$, $D = 15$, and $P = 80\%$.

Database	Se (%)	Sp (%)	PPV (%)	ACC (%)
AFDB	100.00	99.62	100.00	99.84
MITDB	98.59	99.91	99.16	99.79

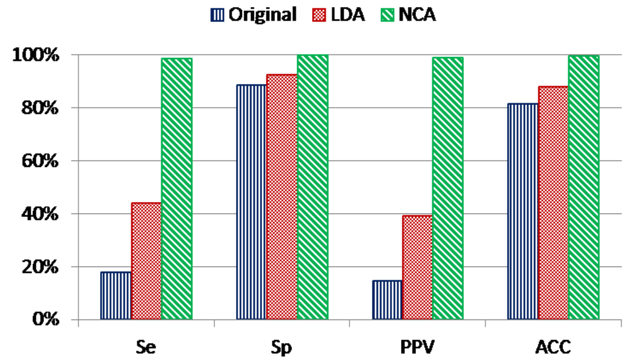

FIGURE 7. Improvement in classification performance owing to the NCA transformation of RRI tachograms.

with the same set of parameters: $m = 11$, $d = 15$, and $p = 80\%$.

V. DISCUSSIONS

Detecting AF by using a short window of RRI tachogram is crucial for development of an effective screening device. The existing methods reported during the past four decades do not made significant improvements when the input signal contains various rhythms. This is because of the two classes not being linearly separable in the original feature space when a window of RRI tachogram is used as a feature vector. Our experiments using state-of-the-art machine-learning techniques yielded poor classification performance in the original feature space using MITDB as shown in Table 5. For example, the NN-classification yielded 80.02% specificity and 97.17% accuracy. The poorer performance of more sophisticated classification models such as the Bayesian classifier and linear discriminate based classifiers (e.g. SVM, ANN, and DLM) are attributed to RRI tachogram window being highly nonlinearly separable features. Although LDA-based linear transformation could be efficient to compute the transformed signal, in fact, experimental results show no significant improvement in classification performance for any classifiers considered, as shown in Table 5. The proposed transformation of a window of the RRI tachogram into an NCA space was effective to improve the robustness of the AF detection, and we obtained significant improvement in AF detection performance as shown in Table 5.

Fig. 7 compares improvements in different performance measures before and after transformations for the Naïve Bayesian classification. It can be observed that the classification performance has improved significantly in the NCA space. In fact, the proposed transformation improved classification performance for all classification models, as shown in Table 5. The Naïve Bayesian method yielded the best performance compared to other classifiers, as shown in Fig. 8.

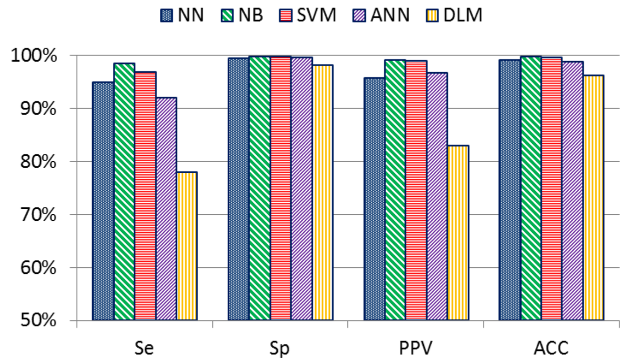

FIGURE 8. Performance of different classification models on the transformed signals in NCA space.

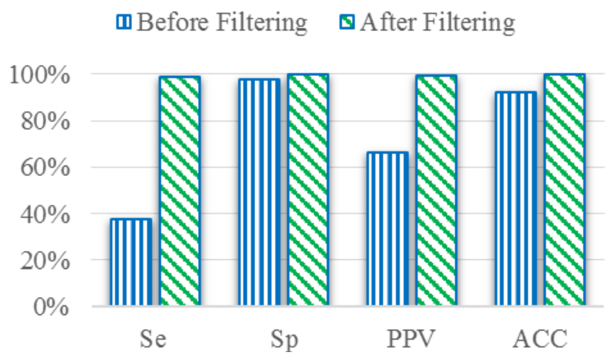

FIGURE 9. Effect of median filtering (ectopic beats removal) on AF detection performance.

Classification performance also depends on different parameters such as the window size of RRI tachogram (d), size of median filter (m), and percentage threshold parameter (p). From Table 2, it could be observed that we can obtain optimal performance using the Naïve Bayesian classifier with a reasonably small window size ($d = 15$). Removal of ectopic beats with media filter has a significant impact on AF detection — the increase of filter size improved the AF detection performance consistently as shown in Table 1. Fig. 9 compares the detection performance without ectopic beats removal (i.e. no filtering of RRI signals) and removal of those beats with a filter size of 11. We have also tested the effect of varying the percentage threshold (p) values. It can be seen from Table 3 that different values of this parameter (from 50% to 100%) do not affect the AF detection performance significantly.

We also compared AF detection performance of landmark methods, using the RRI tachogram as input signal and evaluated on the MITDB, reported in the literature during the past four decades as shown in Table 7. It can be observed that most of these methods utilized thresholding of

TABLE 7. Comparison of AF detection performance of landmark methods using RRI tachogram proposed in the past four decades and evaluated by the challenging MITDB.

Author and year	Classification model	Window size (d)	Se (%)	Sp (%)	PPV (%)	ACC (%)
Moody and Mark [36], 1983	First-order Markov process	20	96.09	-	86.79	-
Dash et al. [28] 2009	Thresholding of Shannon entropy	128	90.02	91.2	-	-
Lian et al. [39] 2011	Thresholding of number of non-empty cells in scatterplot	32 64 128	98.1 97.7 98.9	77.0 78.2 78.8	- - -	- - -
Lee et al. [38], 2013	Thresholding of variance and Shannon entropy	12 128	92.4 91.1	84.1 89.7	- -	- -
Zhou et al. [17, 25], 2015	Thresholding of Shannon entropy	127	97.83	87.41	47.67	88.51
Petrėnas et al. [18] 2015	Thresholding of normalized Heaviside step function	8	97.8	86.4		
Islam et al. [27] 2016	Thresholding of normalized entropy	30 50 70	86.16 86.56 86.22	85.94 86.41 86.40	41.47 42.39 42.24	85.96 86.42 86.38
Jovic and Jovic [16] 2017	Thresholding of alphabet entropy	20 (sec)	96.14	97.10	-	-
Andersen et al. [19] 2019	Combination of convolutional neural and recurrent neural networks	30	98.96	86.04	45.45	87.40
Proposed	NCA transformation & Naïve Bayesian classification	15	98.59	99.91	99.16	99.79

different types of entropy. Although deep-learning methods has been utilized recently but this method did not improve the performance significantly. Rather the proposed NCA transformation with the Naïve Bayesian classification is a simple method which outperforms the existing methods with a large margin. We have also compared the window size used in different method and our method requires a reasonable short window (15 RRIs) to achieve these results. This method is simple and performance is good enough to be incorporated in a mobile screen device.

VI. CONCLUSION

The proposed NCA transformation has improved the AF detection performance significantly, especially when the input signal contains various types of rhythms. This improvement is effective for major state-of-the-art machine-learning-based classification models. This is attributed to the fact that the transformation is able to redistribute the features to make them more separable. This is confirmed by the superior performance of the Naïve Bayesian classification, where we assumed Gaussian distribution of signals in the transformed space. The use of the Naïve Bayesian classification together with the proposed transformation is especially important for the development of a robust method to detect AF using a short window of RRI tachogram to be implementable in a wireless and mobile computing device due to its simplicity. To further investigate the potentiality of the proposed method, we need to incorporate it in a real screening device and validate its performance in practical applications, which are our intended future works. Furthermore, we can extent this work by including other rhythms such as bigeminy in the classification framework.

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MD SAIFUL ISLAM (M'08) received the B.Sc. degree (Hons.) in computer science and engineering from Khulna University, Bangladesh, in 1999, and the Ph.D. degree in computer engineering from Nanyang Technological University, Singapore, in 2007.

He has been an Associate Professor with the College of Computer and Information Sciences, King Saud University (KSU), Saudi Arabia, since September 2017, where he was an Assistant Professor, from 2010 to 2017. Before that, he was a Research Fellow with the School of Computer Engineering, Nanyang Technological University, Singapore. He was an Assistant Professor, from 2006 to 2009, and a Lecturer from the Dhaka University of Engineering and Technology (DUET), Bangladesh, from 2000 to 2006. He has also worked as an Adjunct Faculty Member with the Islamic University of Technology, Dhaka. His current research interests include machine learning, biometrics, and biomedical signal analysis. He is a referee for several international journals.

MOHAMED MAHER BEN ISMAIL received the Ph.D. degree in computer science from the University of Louisville, in 2011. He received the University of Louisville Dean's Citation. He is currently an Associate Professor with the Computer Science Department, King Saud University. His research interests include pattern recognition, machine learning, data mining, and image processing.

OUIEM BCHIR received the Ph.D. degree from the University of Louisville, KY, USA. She is currently an Associate Professor with the Computer Science Department, College of Computer and Information Sciences (CCIS), King Saud University, Riyadh, Saudi Arabia. Her research interests include spectral and kernel clustering, pattern recognition, and hyperspectral image analysis.

MOHAMMED ZAKARIAH received the B.Sc. degree in computer science and engineering from Visvesvaraya Technological University, India, in 2005, and the master's degree in computer engineering from Jawaharlal Nehru Technological University, India, in 2007. He is currently a Researcher with the Computer Science Department, College of Computer and Information Sciences, King Saud University, Riyadh, Saudi Arabia. His research interests include bioinformatics, digital audio forensics, cloud computing, multimedia, healthcare, and social media. He has published more than 20 articles in various reputed journals.

YOUSEF AJAMI ALOTAIBI (S'94–M'97–SM'11) received the B.Sc. degree in computer engineering from King Saud University, Riyadh, Saudi Arabia, in 1988, and the M.Sc. and Ph.D. degrees in computer engineering from the Florida Institute of Technology, FL, USA, in 1994 and 1997, respectively. From 1988 to 1992 and 1998 to 1999, he joined Al-ELM Research and Development Corporation, Riyadh, as a Research Engineer. From 1999 to 2008, he joined the College of Computer and Information Sciences, King Saud University, as an Assistant Professor, where he was an Associate Professor, from 2008 to 2012. Since 2012, he has been a Professor with King Saud University. His research interests include digital speech processing, specially speech recognition, and Arabic language and speech processing.