A Robust Detection Method of Short Atrial Fibrillation Episodes

Zouhair Haddi[1], Jean-François Pons[2], Stéphane Delliaux[3,4], Bouchra Ananou[1], Jean-Claude Deharo[3,5], Ahmed Charaï[2], Rachid Bouchakour[2], Mustapha Ouladsine[1]

[1]Aix Marseille Univ., Univ. Toulon, CNRS, ENSAM, LSIS, Marseille, France
[2]Aix Marseille Univ., Univ. Toulon, CNRS, IM2NP, Marseille, France
[3]Aix Marseille Univ., IRBA, DS-ACI, Marseille, France
[4]APHM, Hôpital Nord, Service des Explorations Fonctionnelles Respiratoires, Pôle cardiovasculaire, Marseille, France
[5]APHM, Hôpital La Timone, Service de Cardiologie du pôle cardiovasculaire et thoracique, Marseille, France

Abstract

This study aimed to detect short-duration Atrial Fibrillation (AF) episodes by studying inter-beat interval time series to reach real-time automatic medical monitoring. Four publicly-accessible sets of clinical data were used for assessment. All time series were segmented in 1-min RR interval windows and then three specific features were calculated, namely, Vector Angular Index, Vector Length Index and Dispersion of points along the perpendicular to the diagonal line. The features of the four databases were merged in order to give rise to huge variability and therefore to better characterize AF rhythm. Principal Component Analysis (PCA) was used to elucidate whether it was possible to discriminate between AF and Normal Sinus Rhythm (NSR) and Learning Vector Quantization (LVQ) neural network has been optimized to develop the classification model. PCA analysis has shown a good discrimination between the studied rhythms. Furthermore, despite its very simple structure, LVQ neural network has performed better on the analysed databases than existing algorithms did, with high sensitivity and specificity respectively of 99.19% and 99.39%.

1. Introduction

Atrial fibrillation (AF), considered as the most common cardiac arrhythmia, is a major public health burden associated with significant morbidity and mortality [1]. In recent years, several algorithms have been developed to detect AF specifically when short duration occurs [2]. Most of them are based on inter-beat interval time series analysis. Although progress in the published results is seen, there is still scope for improvement which needs to be addressed especially for brief duration as short as one minute or less. In this context, Langley et al. [3], have evaluated three features, namely, coefficient of variation, mean successive difference and coefficient of sample entropy for a recording duration of only 10 s. Sensitivities of greater than 94% and specificities of around 93% were achieved. Other assay of entropy was conducted by D.E. Lake et al. [4], in order to assess short AF episodes of 12 beats. Optimal template length and tolerance matching have been carefully checked. The receiver operating characteristic analysis results allowed to reach a sensitivity of 91% and a specificity of 94% for the MIT-BIH dataset. S. Hargittai has investigated the performance of several features, extracted from segments of 80 beats to detect AF [5]. He confirmed that the use of the scatter plot of successive RR differences (dRR Lorenz Plot) and Sample Entropy yielded an overall error rate of about 5% for Physionet datasets (MIT-BIH arrhythmia, atrial fibrillation and long-term atrial fibrillation databases). In the current study, three geometrical features were used, namely, Vector Angular Index (VAI), Vector Length Index (VLI), and dispersion of points along the perpendicular to the diagonal line (SD1) have been exploited as input to PCA and LVQ to diagnosis AF of 1-min episode. These parameters have been previously employed to detect AF [6] by using univariate analysis and were tested on only 60 recordings of AF Termination Challenge Database (80 recordings).

2. Methods

2.1. Databases

PCA and LVQ were evaluated on four publicly-accessible sets of clinical data: AF Termination Challenge

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Database, MIT-BIH AF, Normal Sinus Rhythm RR Interval Database, and MIT-BIH Normal Sinus Rhythm Databases. All time series were segmented in 1-min RR interval windows (total of 47156 and 4902 time series for NSR and AF respectively). Usually, authors trained their algorithms on one of these datasets and tested them on the remaining. We believe that if the four datasets are merged (and categorized into AF and NSR groups), this could give rise to huge variability and therefore to better characterize AF rhythm. To illustrate this idea, we have calculated Vector Angular Index values for AF Termination Challenge Database (Figure 1 (a)) and compared them with those of 1-min AF episodes of the merged datasets (Figure 1 (b)). As it can be seen, there is a clear variability has emerged from the merged datasets.

2.2. R-R time series features

Three features were extracted from the scatter plot (defined as a diagram in which each R-R interval is

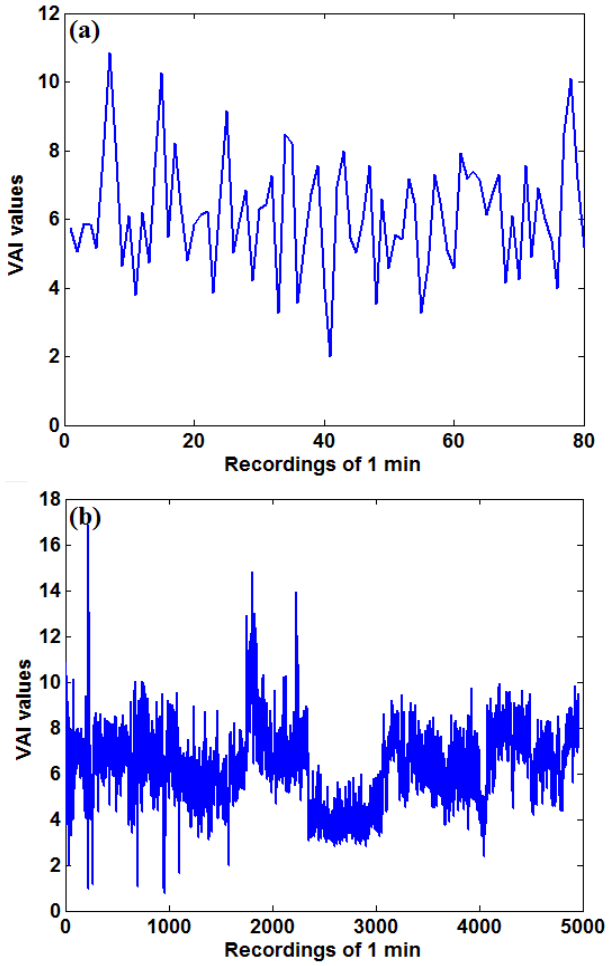

Figure 1. VAI calculated for AF Termination Challenge Database (a) and for 1-min AF episodes of the merged databases (b).

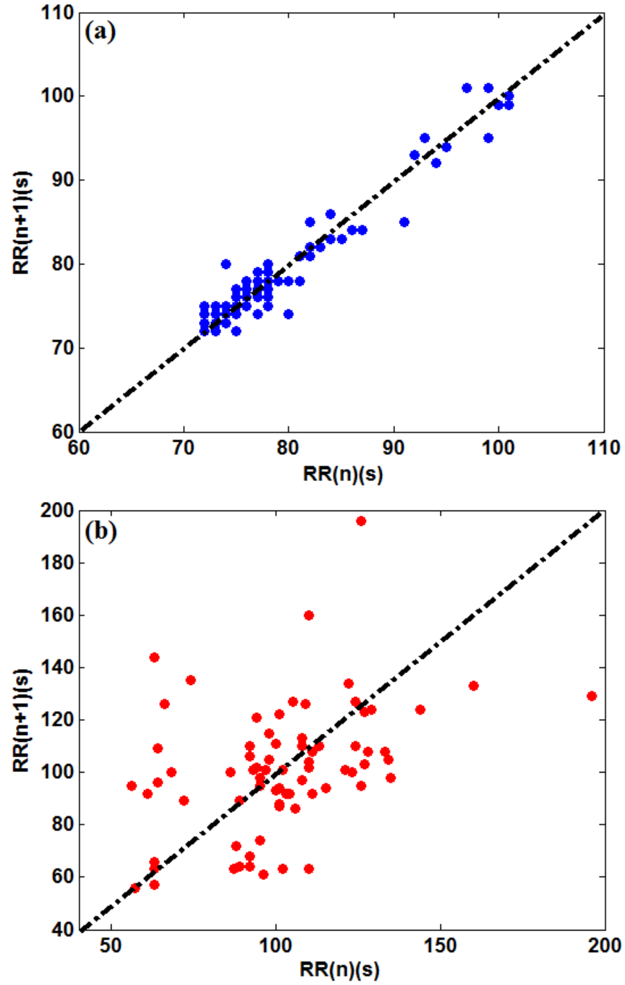

Figure 2. Scatter plots of R-R interval signal of NSR (a), and AF (b).

plotted as a function of the previous R-R interval) to classify AF from NSR. The scatter plot of NSR seems as sticky, in that nearly all the scatter points are centralized along the diagonal line, as shown in Figure 2 (a). However, the scatter plot of AF seems as unfolded fan-shaped, in which all the points are dispersed around the whole plot, as shown in Figure 2 (b). These features, which were first used for univariate analysis by X. Ruan et al. [6] are described as follows:

VAI is calculated as the mean of all the absolute value of angular differences between the lines plotted from every scatter point to the original point and the diagonal line, measuring the angular dispersion of all the points. VLI is calculated as the standard deviation of all distances of scatter points from the original point, measuring the distance dispersion of all the points. They can be defined as:

$$VAI = \frac{\sum_{i=1}^{N} |\theta_i - 45|}{N} \quad (1)$$

$$VLI = \frac{\sqrt{\sum_{i=1}^{N}(l_i - L)^2}}{N} \quad (2)$$

where θ_i is the angle between the line plotted from every scatter point to the original point and the x-axis, l_i is length between every scatter point and the original point, L is the mean of all the l_i, N is the number of scatter points.

SD1 is calculated as the standard deviation of the distances of points from y = x axis, measuring the width of the ellipse and indicating the short-term variability and is defined as:

$$SD1 = STD\left(\frac{|RR_{n+1} - RR_n|}{\sqrt{2}}\right) \quad (3)$$

where RR_n is an R-R interval series with n=1,2,…,N-1, RR_{n+1} is the same as RR_n index-shifted by 1 and $STD(x)$ represents the standard deviation of x.

2.3. Multivariate data analysis

PCA is a very well-known unsupervised method often employed in ECG signal processing [7]. The main objective of PCA consists in expressing the information contained in a dataset by a smaller number of variables called principal components. These principal components are linear combinations of the original response vectors. The principal components are chosen to contain the maximum data variance and to be orthogonal. Hence, PCA allows the reduction of multidimensional data to a lower dimensional approximation, while simplifying the interpretation of the data by the first two or three principal components (PC1, PC2, and PC3) in two or three dimensions and preserving most of the variance in the data [8].

LVQ, introduced by Kohonen [9], is one of prominent learning based algorithms of artificial neural network. This algorithm and its variants have been intensively studied because of their robustness, adaptivity and efficiency. The idea of LVQ is to define class boundaries based on prototypes, a nearest neighbor rule and a winner-takes-all paradigm. The standard LVQ tries to adjust the weights using heuristic error correction rules by minimizing an objective function. The LVQ results are strongly dependent on the initial positions of the prototypes [10].

3. Results and discussion

3.1. PCA analysis results

The PCA score plot was used as an exploratory technique to investigate clustering of data points within the multi-dimensional space of features. The variables were organized in a rectangular matrix as a database. A mean-centering pre-processing technique was applied to the dataset [11]. Figure 2 (a) shows the projections of the 1-min episodes of AF and NSR on a two-dimensional scheme formed by the first two principal components. The values of 89.02% data variance explained by the first PC and 09.41% of data variance explained by the second PC indicate the importance of the first one for pattern separation. This means that the differences existing among AF and NSR episodes along the first axis are more significant than those existing along the second axis. Even if Figure 3 (a) does not show very clear separable groups, Figure 3 (b), which is a zoom-in of the groups borders, demonstrated that a powerful pattern recognition tool could discriminate between AF and NSR rhythm.

3.2. LVQ neural network results

PCA was performed to elucidate whether it was possible to discriminate AF and NSR groups, however, this method cannot be used as proper identification tools.

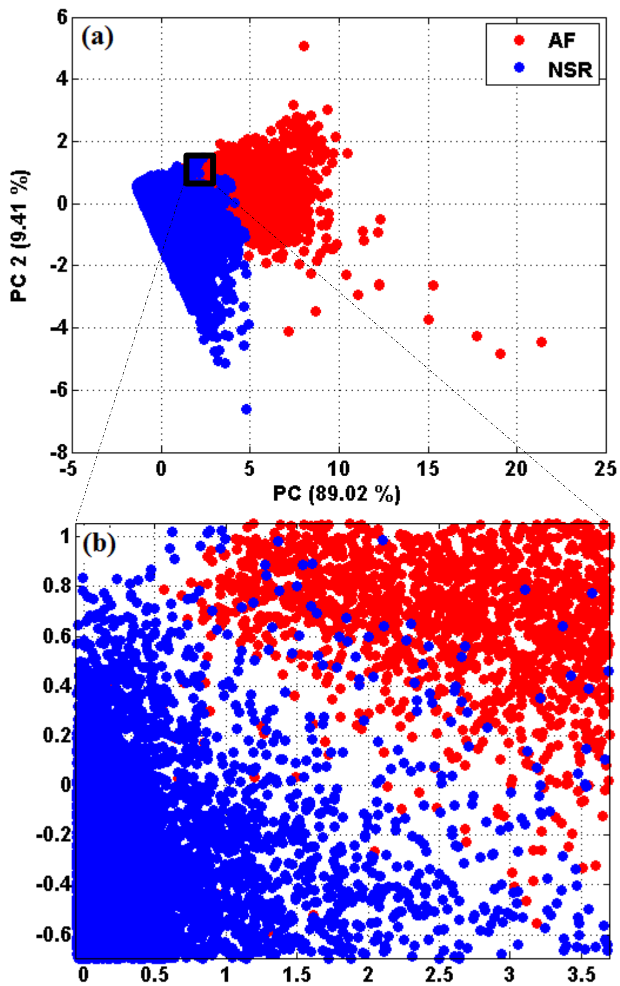

Figure 3. Scores plot of PCA performed on AF and NSR of 1-min episodes.

Since the aim of this work was to identify AF episodes of short duration, LVQ neural network was applied to develop the classifier model. The initial weights of LVQ network were generated randomly just before the learning phase began. Very simple structure (3 neurons for AF and 1 for NSR) has been found to yield very good findings. Since results may be influenced by the selection of the test and training sets, ten test sets (n=17373) were randomly selected. Finally, the selected LVQ classifier has reached a 99.37% success rate in the identification of the AF and NSR groups. Table 1 shows the confusion matrix of the LVQ classifier. Rows indicate true categories and columns predicted categories. As it can be noticed in this table, of 52118 1-min segments of AF and NSR, only 327 mistakes occurred: 40 1-min episodes belonging to AF were misclassified as belonging to NSR, and 287 1-min episodes belonging to NSR were misclassified as belonging to AF. In other words, 99.19% and 99.39% have been reached as sensitivity and specificity respectively.

Table 1. LVQ classification results.

Actual	Predicted	
	AF	NSR
AF	4862	40
NSR	287	46869

4. Conclusion

In this paper, both the PCA and the LVQ neural network classifier are presented as diagnostic tools to facilitate medical decision making in the analysis of AF arrhythmia. The method is based on the analysis of RR-interval time series extracted from ECG recordings. The automated AF detection holds several interesting properties, and can be implemented with only few arithmetical operations which makes it a suitable choice for telecare applications. For future works, we attempt to detect very short AF episodes (less than one min) from RR interval signals.

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Address for correspondence.

Zouhair Haddi
Laboratoire des Sciences de l'Information et des Systèmes (LSIS)
Domaine Universitaire de Saint-Jérôme
Avenue Escadrille Normandie-Niemen
13397 Marseille, France.
zouhair.haddi@lsis.org