ECG Arrhytmias Classification using Data Fusion and Particle Swarm Optimization

Elhoucine BEN BOUSSADA[1], Mounir BEN AYED[2], Adel M.ALIMI[1]
[1]Department of Computer Engineering and Applied Mathematics Department
University of Sfax, National Engineering School of Sfax
Tunisia
[2] Department of Computer Science and Communications
University of Sfax
Faculty of Sciences of Sfax, Tunisia
{houcine.boussada, Mounir.benayed, Adel.alimi}@ieee.org

ABSTRACT: *Computer analysis of electrocardiogram (ECG) data has proven to be an important method to detect cardiac arrhythmias, so that can be of great assistance to the experts in detecting cardiac abnormalities. In this study, we purpose to develop a system to aid in the diagnosis of anomalies cardiac signals. This system is based on data fusion and architected by using the multi-agents system for ECG classification. Therefore, the proposed system helps doctors to quickly and precisely diagnose a heart disease by examining only the class of the ECG beats. In order to achieve the goal of real-time classification, the data used are divided into two datasets: the training set for the unsupervised learning of the classifier and the testing set for the real-time classification. This system is tested on a MITBIH arrhythmia database.*

Keywords: Data Fusion, ECG, Artificial Intelligence, Multi Agent System, PSO, MIT-BIH Database

Received: 13 September 2013, Revised 7 October 2013, Accepted 10 October 2013

1. Introduction

An electrocardiogram (ECG) is a recording of cardiac activity over time. Because of the speed to be placed, especially the efficiency and reliability for diagnostic ECG plays an important role in monitoring and diagnosing patients today. During this ECG is effective only when it is stored on a longterm analysis of such registration requires methods of parameter extraction and automatic classification of heart beats, more efficient and accurate. Many methods have been proposed in recent years both for parameter extraction or classification [4], [5].

Many approaches that automatically classify heart beats have been proposed in the literature. They include statistical [6], [7] and syntactic [8] approaches. Artificial neural networks (ANNs) were also employed to exploit their natural ability in pattern recognition tasks for successful classification of ECG beats [9], [10]. The multilayer perceptron (MLP) is one of the most popular artificial neural networks used in ECG classification. In [9], the principal characteristics of the ECG signal were extracted by using the principal component analysis technique and then were applied to an MLP for classification. Minami et al. [11] used Fourier transform to extract features of QRS complexes and used an MLP with five input and two output cells to classify the features.

Selforganizing maps (SOMs) have also been applied for classifying ECG beats [12], [13]. In [12], SOMs were used to design a customized beat classifier and a global beat classifier. Then, the two classifiers were combined together by the mixture-ofexperts principle. A 5 x 5 SOM was employed for clustering ECG beats into 25 clusters in [13], in which the QRS complexes were represented by the orthogonal Hermite functions. In [14], a multi- channel ART2 neural network was proposed for the classification of two-channel ECG signals. Recently, we have seen a growing number of combined neural network approaches to ECG classification. The neuro-fuzzy network has been used to design the ECG classifier [15], [16]. The neurofuzzy network is composed of two subnetworks connected in cascade: the fuzzy self-organizing layer performing the pre-classification task and the following MLP working as the final classifier. In [17], the MLPs were used at the first level and the second level for the implementation of the combined neural network. Note that there is a very large literature on the subject of classification of heartbeats. A more general overview of this subject can be found in [18], [19], [20].

In this paper, a multi source data fusion agent based model for ECG classification is proposed. This method is based on data fusion agent model [21].

The general architecture of the proposed system is based on multi-agents model used in many fields of research, like in robotics [24].

Multi-source data fusion is a technology combining data from several sources in order to achieve more specific inferences than could be achieved by the use of a single source-data alone. Data fusion systems are now widely used in various areas such as robotics, intelligent system design, video and image processing. Various conceptualizations of the fusion process exist in the literature. The most common and popular conceptualization of fusion systems is the JDL model[1], another general conceptualization of fusion is the work of Goodman et al [2]. One of the most recent and abstract fusion frameworks is proposed by Kokar et al [3].

In order to measure the classification performance, we purpose to use an efficient optimization algorithm: the particle swarm optimization (PSO), so that we compare the classification results before and after the application of the PSO.

PSO is an evolutionary-type computation technique [25], [26]. It deploys a simple mechanism that mimics swarm behavior in birds flocking and fish schooling to guide particles in searching for a global optimal solution.

The remainder of this paper is organized as follows. Section 2 briefly describes the ECG data used in this study. The method for ECG classification and simulation results is shown in section 3 and 4, respectively. Finally, we present in section 5 the conclusion.

2. ECG Description

The Electrocardiogram (ECG) is a graphic record of electrical activity with respect to time that is generated by the human heart [21]. As shown in figure 1, a normal ECG beat contains three basic waves;

• **The P wave:** It is always positive. Its length must be less or equal to 0.12 seconds, and its amplitude does not exceed 2 mm in height. **The PR Interval** varies between 0.12 and 0.20 seconds, and has a tendency to shorten with heart rate.

• **The QRS Complex:** It is always positive. Its duration varies between 0.06 and 0.08 seconds, and must not exceed 0.10 seconds. It decreases slightly when the heart rate increases. **Q** waves, when present, must not exceed 0.04 seconds. The amplitude of the QRS complex usually does not exceed 20 mm in standard leads. This magnitude should not be less than 5mm.

• **The T wave:** It can be positive or negative, but the magnitude of **T** often oscillates between 1 and 4 mm.

The ECG arrhythmia waveforms usually differ with the amplitude and duration of beats. The most important are **QRS complex** changes, so that it was very interesting to use this wave in the diagnosis of cardiovascular diseases. In this paper, we use the QRS complex wave to achieve ECG beat classification.

In this work, the MIT-BIH data base [22] was used the development and the evaluation of the proposed ECG classifier, because it contains a wide variety of noise and artifacts. This data base consists of 48 ECG recordings. Each recording is 30min long. All the 48 recordings were used as the data source in our test. To test the robustness of the proposed classifier, five types of beats including, normal beat (N), premature ventricular contraction (PVC), fusion of ventricular and normal beat (FNB), arterial

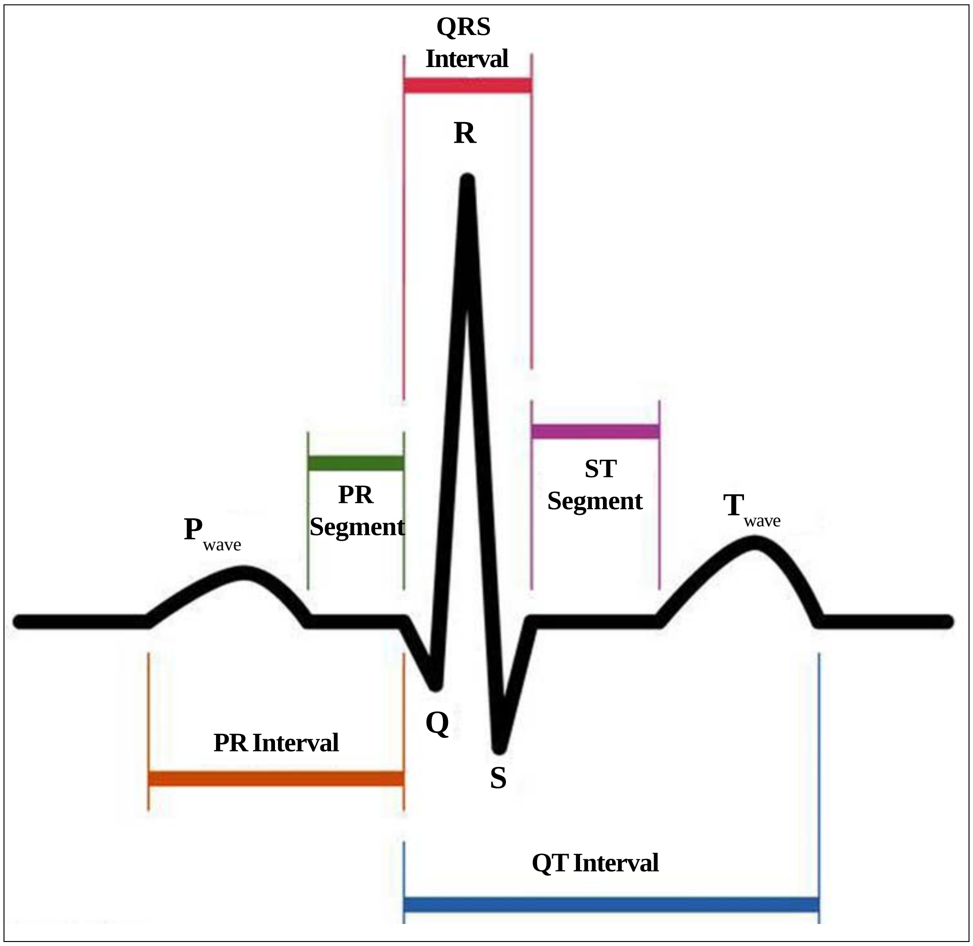

Figure 1. The normal ECG signal contains three basicwaves: P wave, QRS complex, and T wave

premature beat (APB), and right bundle branch block beat (RBB) are selected from the MIT-BIH data base. The table 1 shows the records and the number of beat of each beat type used in this study.

Beat type	records	Number of beats
N	113,119,213,234	836
PVC	119,208,221,223,228,233	605
FNB	208,213	248
APB	209,220,222	165
RBB	212	150

Table 1. Records, Number of Beat and Beat Type

3. ECG Classifier

The main idea of this proposed classifier is based on data fusion and multi-agents system architecture [21]. Figure 2 shows the general block diagram of the proposed system.

Five types of beats including normal beat (N), premature ventricular contraction (PVC), fusion of ventricular and normal beat (FNB), arterial premature beat (APB), and right bundle branch block beat (RBB) are selected from the MITBIH data base.

After the preprocessing and normalization process of data, a training set which contain 100 normalized data for each class is prepared for the training phase of the classification. Then a data fusion multi-agents system evolved with the PSO algorithm by using the training set.

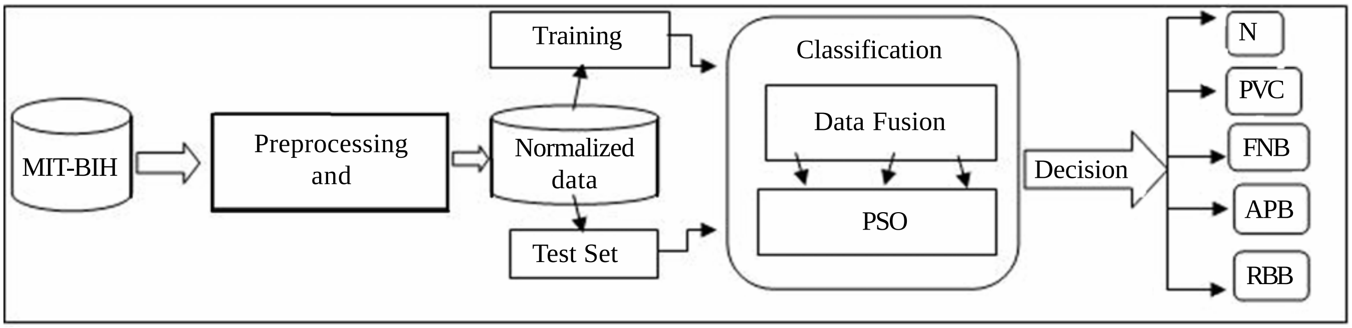

Figure 2. Block diagram of the proposed system

3.1 ECG Data preprocessing

The ECG signal used from MIT-BIH arrhythmia database may contain artifacts, noise and baseline wanders. Therefore it is necessary to clean the ECG signal by removing all these unwanted parts of the signal. After extracting the **R** waves from the selected records, **QRS complex** are normalized by using the following equations [23]:

$$QRSx\,(t) = \frac{\sum_{i=t-7}^{t} QRSx\,(i)}{8} \tag{1}$$

3.2 Data fusion and classification

Multi-sources data fusion, is a relatively new engineering discipline used to combine data from multiple and diverse sources in order to make inferences about events, activities, and situations. These systems are often compared to the human cognitive process where the brain fuses sensory information from the various sensory organs, evaluates situations, makes decisions, and directs action. Among the most common examples where such systems have been developed and widely used, are military systems for threat assessment and weather forecast systems. Generally, data fusion is a process performed on multi-source data towards detection, association, correlation, estimation and combination of several data streams in to one with a higher level of abstraction and greater meaningfulness. The decision given by our system is in the form; N, PVC, FNB, APB, RBB. To the extent of greater precision of the decision given by this system, it well be optimized by Particle Swarm Optimization (PSO).

PSO was first introduced by Kennedy and Eberhart in 1995. It's an optimization technique for difficult optimization problems [25], [26]. A swarm is composed of a set of particles (agents); each particle has its position in the space and its fitness function. The particles are randomly initialized in the search space it moves around to find the optimum solution while taking into consideration the best solution (hear the best data) visited by the individual and by the whole swarm. The fitness function is used to evaluate the performance of each particle. Many algorithms were proposed in this area like IKPSO [27].

In the following we describe the classification method. As shown in figure 1, the proposed system starting with the ECG signal recorded in MIT-BIH arrhythmia database. Firstly it is necessary to begin by the preprocessing stage to remove the noise [23]. After this step, the ECG is subjected to QRS complex detection to detect the R peaks of the ECG beats from the selected records by using the Plan Tompkins algorithm [28]. Secondly the data is normalized by using the equation (1). A training set which contain 100 normalized data for each class is prepared for the training phase of the classification. Then a data fusion system, architected in cooperative multi-agents system, pre-classify the ECG signals and finally a PSO algorithm is involved in this preclassification to give the decision.

4. Experimental Results

The MIT-BIH arrhythmia database contains annotation for both timing information and beat class information manually reviewed by independent experts. The WFDB (Waveform Database) software package with library functions is used for reading digitized signals with annotations. We used the normalized data obtained using the above the preprocessing technique. The reliability factor, (RF) can be calculated with the equation (2): Number of True Class (NTC), Number of False Class (NFC).

$$RF = \frac{NTC}{NTC + NFC} \times 100 \qquad (2)$$

Beat class	RF before PSO (%)	RF after PSO (%)
N	99.256	99.625
PVC	97.768	99.121
FNB	98.638	98.855
APB	97.425	98.625
RBB	96.321	97.124

Table 2. Reliability Factor Results Of ECG Classes

Table 2 lists the results before and after the application of PSO algorithm.

Note that the proposed method classifies the ECG beats with appreciable performance acceptable results.

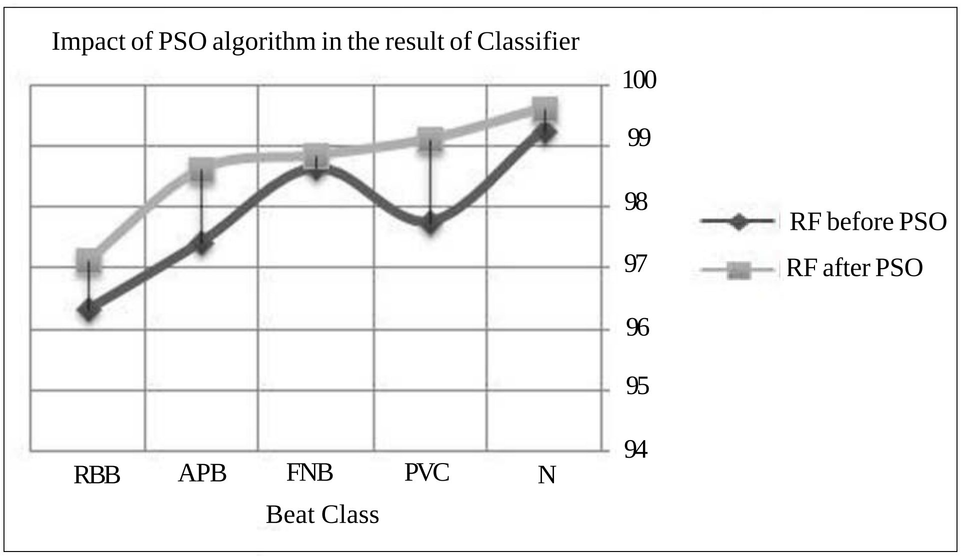

Figure 3. Reabillity factor before and after the application of PSO

As showing in figure 3, the classification performance is better when we use the PSO algorithm to optimize the results of classification.

The application of the PSO algorithm generally increases the results.

5. Conclusion

In this paper we proposed a multi-data source fusion agent based method for ECG classification. The benchmark MITBIH arrhythmia database was used for evaluating the classifier. It is found that this system have an acceptable performance with can be increased by the application of the PSO algorithm.

Although the proposed system can be more developed and compared with others classifier for the same data, all of which are the subject to our future work.

References

[1] White, F. E. (1991). Data Fusion Lexicon, Joint Directors of Laboratories, Technical Panel for C3, Data Fusion SubPanel, Naval Ocean Systems Center, San Diego.

[2] Goodman, I. R., Mahler, R. P. S., Nguyen, H. T. (1997). Mathematics of Data Fusion, Kluwer Academic Publishers, Norwell, MA.

[3] Kokar, M. M., Tomasik, J. A., Weyman, J. (2004). Formalizing classes of information fusion systems, Information Fusion, 5 (3) 189–202.

[4] Ceylan, R.,Ozbay, Y. (2007). Comparisation of FCM, PCA and WT techniques for classification ECG arrhythmias using artificial neural network. Expert systems with Applications, 33, p.286-295.

[5] Yu, S. N., Chen, Y. H. Noise-tolerant electrocardiogram beat classification based on higher order statistics of subband components. Artificial intelligence in medicine, 46, p. 165-178.

De Chazal, P., O'Dwyer, M., Ropella, K. M. (2004). Automatic classification of heartbeats using ECG morphology and heartbeat interval features, *IEEE Transactions on Biomedical Engineering*, 51 (7) 1196–1206.

[6] Engin, M., Fedakar, M., Engin, E. Z., Korürek, M. (2007). Feature measurements of ECG beats based on statistical classifiers, Measurement, 40, p. 904–912.

[7] Tümer, M. B., Belfore II, L. A., Ropella, K. M. (2003). A syntactic methodology for automatic diagnosis by analysis of continuous time measurements using hierarchical signal representations, *IEEE Transactions on Systems, Man, Cybernetics: Part B*, 33 (6) 951–965.

[8] Vargas, F., Lettnin, D., de Castro, M. C. F., Macarthy, M. (2002). Electrocardiogram pattern recognition by means of MLP network and PCA: a case study on equal amount of input signal types, *In*: Proceedings of the VII Brazilian Symposium on Neural Networks.

[9] Engin, M. (2004). ECG beat classification using neurof uzzy network, *Pattern Recognition Letters*, 25 (15) 1715– 1722.

[10] Minami, K., Nakajima, H., Toyoshima, T. (1999). Realtime discrimination of ventricular tachyarrhythmia with Fourier-transform neural network, *IEEE Transactions on Biomedical Engineering*, 46 (2) 179–185.

[11] Hu, Y. H., Palreddy, S., Tompkins, W. J. (1997). A patientadaptable ECG beat classifier using a mixture of experts approach, *IEEE Transactions on Biomedical Engineering*, 44 (9) 891–900.

[12] Lagerholm, M., Peterson, C., Braccini, G., Edenbrandt, L., Sörnmo, L. (2000). Clustering ECG complexes using Hermite functions and self- organizing maps, *IEEE Transactions on Biomedical Engineering*, 47 (7) 838–848.

[13] Fernández-Delgado, M., Ameneiro, S. B. (1998). MART: a multichannel ARTbased neural network, *IEEE Transactions on Neural Networks*, 9 (1) 139–150.

[14] Linh, T. H., Osowski, S., Stodolski, M. (2003). On-line heart beat recognition using Hermite polynom als and neuro-fuzzy network, *IEEE Transactions on Instrumentation and Measurement*, 52, p. 1224–1231.

[15] Engin, M. (2004). ECG beat classification using neurofuzzy network, *Pattern Recognition Letters*, 25 (15) 1715– 1722.

[16] Güler, I., Übeyli, E. D. (2005). ECG beat classifier designed by combined neural network model, *Pattern Recognition*, 38 (2) 199–208.

[17] Wen, C., Lin, T., Chang, K., Huang, C. (2009). Classification of ECG complexes using self-organizing CMAC, Measurement 42, p. 399-407.

[18] Korurek, M., Dogan, B. (2010). ECG beat classification using particule swarm optimization and radial basis fuction neural network, Expert systems with applications, 37, p.7563-7569.

[19] Kiranyag, K. et al. (2011). Personalized long-term ECG classification: A symentic approch, Expert system with applications, 38, p. 3220-3226.

[20] Ben Boussada, E., Mounir, B. A., ALIMI, A. (2012). An intelligent data fusion agent-based model for ECG classification. ICCRK- sousse Tunisia.

[21] http://www.physionet.org/cd-updates/#mit-biharrhythmia- database-cd-rom.

[22] korurek, M., & Nizam, A. (2008). A new arrythmia clustering technique basez on ant colony optimization, *Journal of biomedical informatics*, 41, p. 874-881.

[23] Nizar. Rokbani, Ben Boussada, E., Ammar, B., Adel M. Alimi. (2009). From gaits to ROBOT, A Hybrid methodology for A biped Walker, Clawar 09, Conference on climbing and walking robots, Turkey, p. 685-692.

[24] Nizar. Rokbani, Ben Boussada, E., Adel M. Aiimi. (2008). Particle Swanns Optimization, for humanoid walking-gaits generation, Advances in Mobile Robotics, *World scientific*, September, p. 744- 751.

[25] Nizar Rokbani, Ben Boussada, E., Boudour Ammar, Adel M. Alimi. (2010). Biped Robot Control Using Particle Swarm Optimization, IEEE SMC, p. 506 – 512.

[26] Nizar Rokbani, Adel M Alimi. (2012). IK-PSO, PSO Inverse Kinematics Solver with Application to Biped Gait Generation. *International Journal of Computer Applications*, 58 (22) 33-39, Published by Foundation of Computer Science, New York, USA.

[27] Pan, Jiapu, Tompkins, Willis. (1985). A real-time QRS detection algorithm, Biomedical Engineering, *IEEE Transaction on BME*-32, p. 230-236