Combination of Different Classifiers for Cardiac Arrhythmia Recognition

M. R. Homaeinezhad, E. Tavakkoli, M. Habibi, S. A. Atyabi, A. Ghaffari

Abstract—This paper describes a new supervised fusion (hybrid) electrocardiogram (ECG) classification solution consisting of a new QRS complex geometrical feature extraction as well as a new version of the learning vector quantization (LVQ) classification algorithm aimed for overcoming the stability-plasticity dilemma. Toward this objective, after detection and delineation of the major events of ECG signal via an appropriate algorithm, each QRS region and also its corresponding discrete wavelet transform (DWT) are supposed as virtual images and each of them is divided into eight polar sectors. Then, the curve length of each excerpted segment is calculated and is used as the element of the feature space. To increase the robustness of the proposed classification algorithm versus noise, artifacts and arrhythmic outliers, a fusion structure consisting of five different classifiers namely as Support Vector Machine (SVM), Modified Learning Vector Quantization (MLVQ) and three Multi Layer Perceptron-Back Propagation (MLP–BP) neural networks with different topologies were designed and implemented. The new proposed algorithm was applied to all 48 MIT–BIH Arrhythmia Database records (within–record analysis) and the discrimination power of the classifier in isolation of different beat types of each record was assessed and as the result, the average accuracy value Acc=95.51% was obtained. Also, the proposed method was applied to 6 number of arrhythmias (Normal, LBBB, RBBB, PVC, APB, PB) belonging to 20 different records of the aforementioned database (between–record analysis) and the average value of Acc=95.6% was achieved. To evaluate performance quality of the new proposed hybrid learning machine, the obtained results were compared with similar peer–reviewed studies in this area.

Keywords—Feature Extraction, Curve Length Method, Support Vector Machine, Learning Vector Quantization, Multi Layer Perceptron, Fusion (Hybrid) Classification, Arrhythmia Classification, Supervised Learning Machine.

I. INTRODUCTION

Signal processing and data mining tools have been developed to enhance the computational capabilities so as to help clinicians in diagnosis and treatment. The ECG is a representative signal containing information about the condition of the heart. The shape and size of the P–QRS–T cycles and the time intervals between various peaks possess useful information about the nature of disease afflicting the heart.

However, the human observer cannot directly monitor these subtle details. Besides, since biosignals are highly subjective, the symptoms may appear at random in the timescale. The presence of cardiac abnormalities is generally reflected in the shape of ECG waveform and heart rate. Therefore, study of ECG pattern and heart rate variability has to be carried out over extended periods of time, [1]. If according to any happening, the electro–mechanical function of a region of myocytes fails, the corresponding abnormal effects appear in the ECG which is an important part of the preliminary evaluation of a patient suspected to have a heart–related problem. Generally, each heart–beat type classification algorithm consists of four sequential computational levels: a) pre–processing stage, b) detection–delineation stage, c) appropriate signal segmentation and feature selection–computation stage and d) selection and design of an efficient recognition algorithm as well as feature space dimension enhancement. Based on a comprehensive literature survey among many documented works, it is seen that several features and extraction (selection) methods have been created and implemented by authors. For example, short time Fourier transform (STFT) [7], fast Fourier transform (FFT) [8–9], original ECG signal [10], preprocessed ECG signal via appropriately defined and implemented wavelet transform [11], statistical moments [12], nonlinear transformations such as Liapunov exponents and fractals [13–15], higher order spectral methods [16–17], power spectral density (PSD) [18–19], Hilbert transform (HT) [20], have been used as appropriate sources for feature extraction. In order to extract feature(s) from a selected source, various methodologies and techniques have been introduced. To meet this end, the first step is segmentation and excertion of specific parts of the preprocessed trend (for example, in the area of the heart arrhythmia classification, ventricular depolarization regions are the most used segments). Afterwards, appropriate and efficient features can be calculated from excerpted segments via a useful method. Up to now, various techniques have been proposed for the computation of feature(s). For example mean, standard deviation, maximum value to minimum value ratio, maximum–minimum slopes, summation of point to point difference, area, duration of events, correlation coefficient with a pre-defined waveform template, statistical moments of the auto (cross) correlation functions with a reference waveform [21], mutual information [22–23], bi–spectrum [24] may be used as an instrument for calculation of features. After generation of the feature source, segmentation, feature selection and extraction (calculation), the resulted feature vectors should be divided into two groups “train” and “test” for tuning of an appropriate classifier such as a neural network [25–28],
support vector machine [29], pnn [30], knn [31], fuzzy network [32–35] or ANFIS, [36–37].

**Organization of This Study.** The general block diagram of the proposed heart arrhythmia recognition–classification algorithm including two train and test stages is shown in Fig. 1. According to this figure, first, the events of the ECG signal are detected and delineated using a robust wavelet-based algorithm [38–39]. Then, each QRS region and also its corresponding DWT are supposed as virtual images and each of them is divided into eight polar sectors. Next, the curve length of each excerpted segment is calculated and is used as the element of the feature space for the aim of increasing the robustness of the proposed classification algorithm versus noise, artifacts and arrhythmic outliers, a fusion structure consisting of five different classifiers namely as SVM, MLVQ and three MLP–BP neural networks with different topologies were designed and implemented. The new proposed algorithm was applied to all 48 records of the MITDB and the average value of Acc=98.18% was obtained. Also, the proposed hybrid classifier was applied to 6 number of arrhythmias (Normal, left bundle branch block–LBBB, right bundle branch block–RBBB, premature ventricular contraction–PVC, atrial premature beat–APB, paced beat–PB) belonging to 20 number of the MITDB and the average value of Acc=95.6% was achieved.

To compare the outcomes of this study with previous peer-reviewed studies and to show the generalization power of the proposed classification algorithm, 500 samples have been selected for training and 40,438 samples for testing groups. Finally, some comparisons between existing peer-reviewed studies and the presented work aimed for validating the proposed classification algorithm, 500 samples have been selected for training and 40,438 samples for testing groups. The new proposed algorithm including two train and test stages is shown in Fig. 1. The general block diagram of an ECG beat type recognition algorithm supplied with the virtual image–based geometrical features

If the scale factor $a$ and the translation parameter $b$ are chosen as $q = 2$ i.e., $a = 2^k$ and $b = 2^k l$, the dyadic wavelet with the following basis function will be resulted [40],

$$
\psi_{k,l}(t) = 2^{-k/2} \psi(2^{-k} t - l); \quad k, l \in Z^+
$$

To implement the à trous wavelet transform algorithm, filters $H(z)$ and $G(z)$ should be used according to the block diagram represented in Fig. 2-a, [40]. According to this block diagram, each smoothing function (SMF) is obtained by sequential low–pass filtering (convolving with $G(z)$ filters), while after high–pass filtering of a SMF (convolving with $H(z)$ filters), the corresponding DWT at appropriate scale is generated. In order to decompose the input signal $x(t)$ into different frequency passbands, according to the block diagram of Fig. 2-b, sequential high–pass low–pass filtering including down–sampling should be implemented. The filter outputs $x_H(t)$ and $x_L(t)$ can be obtained by convolving the input signal $x(t)$ with corresponding high–pass and low–pass finite–duration impulse responses (FIRs) and contributing the down–sampling as

$$
\begin{align*}
    x_L(t) &= \sum_{k=-\infty}^{+\infty} g(k) x(2t - k) \\
    x_H(t) &= \sum_{k=-\infty}^{+\infty} h(k) x(2t - k)
\end{align*}
$$

On the other hand, to reconstruct the transformed signal, the obtained signals $x_H(t)$ and $x_L(t)$ should first be up–sampled by following simple operation
\[
\begin{align*}
\begin{cases}
x_L^t(2t) = x_L(t), \quad x_L^t(2t+1) = 0 \\
x_H^t(t) = x_H(t), \quad x_H^t(2t+1) = 0 \\
t = 0, 1, \ldots, N-1
\end{cases}
\end{align*}
\]

If the FIR lengths of the \(H(z)\) and \(G(z)\) filters are represented by \(L_H\) and \(L_G\) respectively, then the reconstructing high-pass and low-pass filters are obtained as

\[
\begin{align*}
g^*(t) &= g(L_G - 1 - t) \\
h^*(t) &= H(L_H - 1 - t)
\end{align*}
\]

Then, the reconstructed signal \(x_R(t)\) is obtained by superposition of the up–sampled signals convolved with their appropriately flipped FIR filters as follow

\[
x_R(t) = \sum_{k=-\infty}^{\infty} h^*(k)x_H^t(t-k) + \sum_{k=-\infty}^{\infty} g^*(k)x_G^t(t-k)
\]

For a prototype wavelet \(\psi(t)\) with the following quadratic spline Fourier transform,

\[
\Psi(\Omega) = j\Omega \left( \frac{\sin(\Omega/4)}{\Omega/4} \right)^4
\]

the transfer functions \(H(z)\) and \(G(z)\) can be obtained from the following equation

\[
\begin{align*}
H(e^{j\omega}) &= e^{j\omega/2}(\cos(\omega/2))^3 \\
G(e^{j\omega}) &= 4je^{j\omega/2}(\sin(\omega/2))
\end{align*}
\]

and therefore,

\[
\begin{align*}
h[n] &= (1/8)\delta[n+2] + 3\delta[n+1] + 3\delta[n] + \delta[n-1] \\
g[n] &= 2(\delta[n+1] + \delta[n])
\end{align*}
\]

After numerous empirical investigations, it was concluded that for frequency contents of up to 50 Hz, à trous algorithm can be used in different sampling frequencies. Therefore, one of the most prominent advantages of à trous algorithm is the approximate independency of its results from sampling frequency. This is because of the main frequency contents of the ECG signal concentrate on the range less than 40 Hz [38–39]. After examination of various databases with different sampling frequencies (range between 136 to 10 kHz), it has been concluded that in low sampling frequencies (less than 1000 Hz), scales \(2^\lambda\) (\(\lambda = 1, 2, \ldots, 5\)) are usable while for sampling frequencies more than 1000 Hz, scales \(2^\lambda\) (\(\lambda = 1, 2, \ldots, 8\)) contain profitable information that can be used for the purpose of wave detection, delineation and classification.

### III. Modified Learning Vector Quantization Algorithm

1) Conventional LVQ: The conventional LVQ algorithm is a learning machine which requires no hidden layer and possesses a m-neuron and a n-neuron input and output layers, respectively. The number of input layer neurons is equal to feature space dimension while the number of output layer neurons is equal to the number of classes forming the feature space. Each neuron of the input layer is attached to all neurons of the output layer via a connection and a scalar weight is associated with each connection (Fig. 3). The weight between node i of the input layer and node j of the output layer is indicated by \(w_{ij}\). According to the LVQ algorithm, to fulfill the train stage, if the k-th input feature vector \(x_k\) is applied to the network, then an appropriately defined distance of the feature vector with the weights terminating to the j-th output layer neuron is calculated as follows

\[
\begin{align*}
D(j, k) &= f(x_k, w_j) \\
w_j &= \{w_{ij} \mid i = 1, 2, \ldots, m\}
\end{align*}
\]

Where \(f(x_i, x_j)\) is a scalar distance function. For instance, \(f(x_i, x_j)\) can be defined as

\[
\begin{align*}
(a) \quad f(x_i, x_j) &= (x_i - x_j)^T\Sigma(x_i - x_j) \\
(b) \quad f(x_i, x_j) &= (\sum_{k=1}^{p}(x_i(k) - x_j(k)))^{1/r} \\
(c) \quad f(x_i, x_j) &= \frac{1}{p} \sum_{k=1}^{p} abs(x_i(k) - x_j(k))
\end{align*}
\]

Where the first term of the Eq. 12 called generalized distance and for the weight matrix \(\Sigma = I\) the famous Euclidean norm will be achieved. While the second term of the Eq. 12 is called Minkowski distance of degree \(r\) and for \(r = 2\), again the Euclidean distance appears. The third term of Eq. 12, is called the City Block distance and is used in many pattern recognition cases. If \(D_T(k)\) indicates an array including distances of the feature vector \(x_k\) from all output layer neurons, then, the label of this feature vector is predicted by the following criterion

\[
\hat{\delta}(k) = \delta(\min \{D_T(k)\})
\]

\[
D_T(k) = \{D(j, k) \mid j = 1, 2, \ldots, n\}
\]
If the predicted label $\hat{\delta}(k)$ is true, the minimum distance of the array $D_T(k)$ is decreased by learning rate proportionally. On the other hand, if $\delta(k)$ is false, then the minimum distance of the array $D_T(k)$ is increased by the same learning rate as

$$
\min (D_T(k)) = \min (D_T(k)) - \eta \min (D_T(k))
$$

if $\delta(k)$ is True

$$
\min (D_T(k)) = \min (D_T(k)) + \eta \min (D_T(k))
$$

if $\delta(k)$ is False

(14)

2) Modified Learning Vector Quantization (MLVQ): Suppose that $w_{ij}$ indicates an array including $l_j$ scalar weights and the indices $i, j$ are pointers to the $i$-th neuron in the input and $j$-th neuron in the output layers, respectively. If each array $w_{ij}$ is put into a matrix, the weight matrix $W_j$ will be resulted. In order to formulate the MLVQ algorithm, first it is noted that $j = 1, 2, \ldots, N_c$ shows the class index, $N_c$ is the number of classes and $p$ is the dimension of the feature space.

If each column of the weight matrix $W_j$ is indicated by $C_k(j)$ $(k = 1, 2, \ldots, l_j)$ and $f_n$ is a train feature vector, then the distance between $f_n$ and all $C_k(j)$ arrays can be obtained as

$$
d_{kn}^{(j)} = (C_k(j) - f_n)^T \Sigma (C_k(j) - f_n)
$$

Where, $\Sigma$ is a weighting matrix and for $\Sigma = I$, the quadratic form is obtained. In this case, the array $D_n^{(j)}$ including all distances between vector $f_n$ and $C_k(j)$ is created. So, the predicted label $\hat{\delta}$ of feature vector $f_n$ can be determined as follow

$$
D_n^{(j)} = \{d_{kn}^{(j)}, \ldots, d_{ln}^{(j)}\}
$$

$$
\hat{\delta} = \delta \left\{ \min \{D_n^{(1)}, \min (D_n^{(2)}), \ldots, \min (D_n^{(N_c)}) \} \right\}
$$

(17)

Where $\delta(0)$ is the associated true label operator of the input argument. If the predicted label is true, then the column $C_k(j)$ is decreased by learning rate $\eta$ while if the predicted label is not true, that column is increased by the same learning rate and can be written as

$$
d_{qn}^{(\delta)} = Arg \min (d_{kn}^{(\delta)}, \ldots, d_{ln}^{(\delta)})
$$

$$
C_q^{(\delta)} = C_q^{(\delta)} - \eta d_{qn}^{(\delta)} \text{ if } \hat{\delta}(k) \text{ is True}
$$

$$
C_q^{(\delta)} = C_q^{(\delta)} + \eta d_{qn}^{(\delta)} \text{ if } \hat{\delta}(k) \text{ is False}
$$

(19)

As an interpretation for Eqs. 15 to 19, by inserting feature vector $f_n$, all pre-defined distances between this vector and all weight vectors between input and output layers are calculated and as the result, the $f_n$ is considered to belong to the class including minimum distance between all weights and all output neurons. If this classification is true, the minimum distance is decreased by learning rate $\eta$ while if the outcome of the classification is false, the minimum distance will be increased by $\eta$. By this learning strategy, desirable results for the selection of the best weight vector and error increasing rate versus epoch number will be attained. The accuracy of the MLVQ network depends upon the following parameters:

- **The Number of Train Epochs.** Generally, more epoch number results better accuracy and the epochs can be considered to have inverse proportionality with number of weights $l_j$, i.e., the network with larger $l_j$ will requires fewer epochs for reaching an acceptable accuracy. Although, a trade-off between the number of $l_j$ and epochs number can be found for covering the stability-plasticity dilemma.

- **The Number of Weights Assigned to Each Connection.** In the conventional LVQ method if the number of train data is a large value, the weights lying in connections should adapt themselves with several data types and probable outliers and therefore, a weak performance might be expected. In other words, if by entering a new feature vector to the network, the training strategy pushes the incorporated weights toward forgetting the previously learned information, the stability-plasticity dilemma will appear. To solve this problem, more weights can be assigned to each connection. To this end, one way is to increase the number of the output layer neurons and considering more than one node for each class. Although, by this modification the overall accuracy of the network may increase, however, a malformed topology with high computational burden will be achieved. As the second way, instead of assigning a scalar weight to each connection, a vector including some weights is considered between each input-output neurons connection.

- As final comment for the MLVQ method, if the a priori probabilities associated with the feature space classes are not equal, in regulation of the weight vector ending to the class with maximum probability, the corresponding neuron of this class will win predominatingly and correspondingly the winning Euclidean norm is permanently decreased. Thus, after passing a large number of train data from the network, in the test stage, inputted features will falsely being guided to this node and consequently the cumulative accuracy is corrupted. To solve this problem, a modified learning rate is proposed as follow

$$
\eta_m = \begin{cases} 
\eta \frac{M_l}{M_s} (1 - \frac{M_m}{M_s}) \text{ if } \hat{\delta}(k) \text{ is True} \\
\eta \frac{M_m}{M_s} (1 - \frac{M_l}{M_s}) \text{ if } \hat{\delta}(k) \text{ is False}
\end{cases}
$$

(20)

Where, $M, M_m$ and $M_L$ are the data numbers of the train, the largest and the smallest classes, respectively.

A. Radial Basis Function based Support Vector Machine (RBF–SVM) Classifier

In this work, RBF–SVM is implemented as arrhythmias classification method. According to Vapnik formulation [41], if couple $(x_i, \delta(x_i))$ (in which $\delta(x_i)$ is class function, $i = 1, 2, \ldots, N$) describing data elements and their corresponding categories which are linearly separable in the feature space, then

$$
f(x) = w^T \phi(x) + b
$$

(21)
where \( w \) is weight vector, \( b \) is bias term and the condition \( f(x_i)\delta(x_i) > 0 \) holds. On the other hand, if train data is not linearly separable in the feature space to find a suitable separating hyper plane, the following constrained optimization problem should be solved

\[
\text{CoF}(w, \zeta) = \frac{1}{2} ||w||^2 + C \sum_{i=1}^{N} \zeta_i \\
s.t. \quad \delta(x_i) (w^T \phi(x_i) + b) \geq 1 - \zeta_i, \quad i = 1, 2, \ldots, N
\]

(22)

Where \( \text{CoF} \) is a cost function. Upon solving the above constrained optimization problem, separating hyper plane will be obtained. In the above equation, \( C \) is called regularization parameter which its value generates a trade-off between hyperplane margin and classification error. \( \zeta \) is slack parameter corresponds to \( x_i \). Introducing Lagrange multipliers as

\[
\text{CoF}(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j \delta(x_i) \delta(x_j) \\
K(x_i, x_j) s.t. \quad \sum_{i=1}^{N} \alpha_i \delta(x_i) = 0, \quad 0 \leq \alpha_j \leq C
\]

(23)

Where \( K(x_i, x_j) \) is kernel function obtained from following equation

\[
K(x_i, x_j) = \phi^T(x_i)\phi(x_i)
\]

(24)

Fig. 3. An mn MLVQ network topology for a m–dimensionality feature space and n-type categories

More details about fundamental concepts of SVM can be found in [41].

IV. QRS GEOMETRICAL FEATURES EXTRACTION

A. ECG Events Detection and Delineation

In this step, QRS complexes are detected and delineated. Today reliable QRS detectors based on Hilbert [42–43] and Wavelet [38–39] transforms can be found in literature. In this study, an ECG detection–delineation method with the sensivity and positive predictivity \( Se = 99.95\% \) and \( P+ = 99.94\% \) and the average maximum delineation error of 6.1 msec, 4.1 msec and 6.5 msec for P–wave, QRS complex and T–wave, respectively is implemented [38]. By application of this method, detecting the major characteristic locations of each QRS complex i.e., fiducial, R and J locations, becomes possible.

B. Detected QRS Complex Geometrical Features Extraction

[44]

In order to compute features from the detected QRS complexes either normal or arrhythmical via the proposed method, first a reliable time center should be obtained for each QRS complex. To find this point, the absolute maximum and the absolute minimum indices of the excerpted DWT dyadic scale \( 2^i \) using the onset–offset locations of the corresponding QRS complex, are determined. It should be noted that according to comprehensive studies fulfilled in this research, the best time center of each detected QRS complex is the mean of zero-crossing locations of the excerpted DWT (see Fig. 4).

To make a virtual close–up from each detected QRS complex, a rectangle is built on the complex with following specifications:

- The left–side mid–span (longitudinal direction) of the rectangle is the fiducial location of the QRS complex.
- The maximum absolute vertical distance of the complex from the fiducial point is the half of the rectangle height.
- The center of rectangle is the time-center of the QRS complex.
- The right-hand abcissa of the rectangle is the distance between QRS time center and its J–location.

Fig. 4. Determination of the time center of a detected QRS complex using excerpted DWT scale \( 2^4 \)
Afterwards, Each QRS region and also its corresponding DWT are supposed as virtual images and each of them is divided into eight polar sectors. Next, the curve length of each excerpted segment is calculated and is used as element of the feature space, (therefore, for each detected QRS complex, 16 features are computed). The quantity curve–length of a hypothetical time series $x(t)$ in a window with length $W_L$ samples can be estimated as

$$M_{CL} \approx \frac{1}{F_s} \sum_{t=k}^{k+W_L-1} \sqrt{1 + \left[ (x(t+1) - x(t)) / F_s \right]^2}$$  \hspace{1cm} (27)$$

Where, $F_s$ is sampling frequency of the time series $x(t)$. The curve length is suitable to measure the duration of the signal $x(t)$ events, either being strong or weak. Generally, the $M_{CL}$ measure indicates the extent of flatness (smoothness or impulsive peaks) of samples in the analysis window. This measure allows the detection of sharp ascending/descending regimes occurred in the excerpted segment [39]. A generic example of a holter ECG and its corresponding $2^4$ DWT dyadic scale with the virtual images of the complexes provided for feature extraction as well as two quantities obtained from the RR–tachogram are shown in Fig. 5.

V. DESIGN OF THE HYBRID (FUSION) NEURO-SVM-MLVQ CLASSIFICATION ALGORITHM

Several differences exists in the structure and operating mechanisms of diverse classification algorithms such as Artificial Neural Network (ANN), MLVQ and SVM. Reasonably, achieving exactly similar result from them for given common train and test feature spaces, cannot be expected. Assessments confirm that in the arrhythmia classification from the MITDB beat–types, if two classifiers belonging to different recognition families are appropriately trained, a uniform difference between their operating characteristics versus records cannot be found. In other words, the performance characteristics of two different classifiers show recognition diversity opposed to changing the record number. For instance, suppose that a SVM and a MLP–BP are trained with record 105 of the MITDB. In this case the SVM and the MLP–BP accuracies are calculated as 97.02% and 94.32%, respectively. However, by using of record 221 of the MITDB, the obtained accuracies are 97.97% and 98.17%, respectively indicating the existence of diversity between the SVM and the MLP classifiers. In order to increase the total accuracy of the proposed classification algorithm, one way is to synthesize the output of several classification algorithms with different inherent structures to achieve the best possible accuracy leading to higher robustness against uncertainties and probable arrhythmia or outliers. In this study, to build a fusion (hybrid) classification scheme, five types of different classification methods namely as SVM, MLVQ and three MLP–BP networks with different topologies were properly regulated using the train dataset. The specifications of each classification algorithm are described below.

- **SVM Classifier.** According to section B.3, each SVM includes two parameters $C$ and $\gamma$ that should be tuned properly to achieve satisfactory accuracies. In this study the best choices for the parameters $C$ and $\gamma$ were concluded to be 10 and 0.000001, respectively. The predicted labels of the input feature vector were considered as the output of this classifier in the fusion structure.

  - **MLVQ Classifier.** As mentioned previously in section B.2, this classifier doesn’t require any hidden layer. For this topology, learning rate (LR), number of weights assigned to each connection and maximum epoch number (MEN) were chosen 0.01, 4 and 3000, respectively.

  - **MLP*-BP1.** The first MLP–BP classifier includes one
hidden layer with number of hidden layer neurons (NHLN) equal to 17, tangent sigmoid and the logarithmic sigmoid as the activation functions of the hidden layer and output layer, respectively. Also, for this ANN, MEN is chosen to be 200.

- **MLP–BP2.** This classifier possesses one hidden layer with NHLN=15. The tangent sigmoid was chosen as the activation function for both hidden and output layers, respectively. For this ANN, MEN = 300 was assigned.

- **MLP–BP3.** The third ANN-type classifier has one hidden layer with NHLN=18 and logarithmic sigmoid for both the hidden and the output layers. In this case MEN=1000 was chosen.

It should be noticed that several parameters such as types of activation functions and several values for NHLN, MEN were examined and were altered based on trying–and–error method and suitable ranges and types were chosen for these parameters. From each classifier embedded into the fusion structure, following outputs are processed

- Predicted labels for train and test feature space.
- Accuracy of the classifier

The predicted labels of each particle classification algorithm are used for creation of a hybrid classifier consisting of a MLVQ, a SVM and three MLP–BP types ANN classifiers. To build a fusion classification, in this study, the predicted label of each classifier for the k-th test input is put in the vote array \( G(k) \) as follows

\[
G(k) = \{p(i, k) \mid i = 1, 2, \ldots, 5 \} \tag{28}
\]

Where \( p(i, k) \) is the label predicted by the i-th classifier of the fusion algorithm for the k-th test input. To estimate the label of test input, the value with the most iteration in \( G(k) \) is selected as a label of test input (see Fig 6).

To evaluate performance of the proposed feature extraction method and the fusion classification algorithm, the following steps are pursued

- Evaluation of the discrimination power of the selected features.
- Design of the particle classifiers and their implementation to all MITDB records.
- Design of the fusion classifier for each MITDB record and comparing the obtained results with each particle classifier.
- Selection of some rhythms from the MITDB records and designing of the particle and fusion classifiers.
- Comparison of the final obtained results with the previous similar peer-reviewed studies.

### VI. VALIDATION OF HYBRID NEURO-SVM-MLVQ CLASSIFICATION ALGORITHM

In table 1, the numeric codes of the 23 MITDB rhythms (beat–types) and their corresponding annotations are illustrated. After implementation of the MLVQ, SVM and three MLP–BP neural network classifiers and the corresponding fusion classifier to all 48 MITDB records and calculation of the accuracy, the obtained results are shown in table 2. According to this table, the fusion classifier yielded the average accuracy of Acc=98.51% given all data and all rhythms of the MITDB records (within–record analysis). As it can be seen in this table, the overall performance quality associated with the fusion classification algorithm is superior rather than the structural classifiers embedded in the body of the hybrid algorithm. It should be noted that although in some records of the MITDB, one or more particle classifiers might have better performance rather than the fusion classifier, but this behavior doesn’t continue uniformly for all records and hence the superiority of the fusion scheme is justified.

In order to be able for comparing the obtained results of this study with Melgani–Bazi [29] utilizing exactly the same train and test databases is mandatory. To this end, records 100, 102, 104, 105, 106, 107, 118, 119, 200, 201, 202, 203, 205, 208, 209, 212, 213, 214, 215 and 217 are selected from the MITDB records and the rhythms Normal, LBBB, RBBB, PVC, APB and PB are extracted according to the MITDB annotation files. In table 3, the name of the MITDB records as well as the selected beat–types and their corresponding beat numbers are presented.

#### A. Error-Rate Analysis

It should be noted that if some diversely designed classification algorithms show error rate diversity relative to each
In Table 4 and Table 5, results of Melgani–Bazi [29] and the proposed hybrid classifier for each class are demonstrated. In Fig. 7, the error rate diversities of structural classifiers in order to show the marginal performance improvement of each classifier are presented. In Table 6, the performance of the fusion classification algorithm is assessed relative to other high-performance recent works. In this table, it is assessed whether it is possible to identify correctly the number of classes of each beat. Table 6 illustrates the fusion of this table with Melgani–Bazi [29] and result of this study is presented, respectively. Table 7, the performance of the fusion classification algorithm has been described by the obtained confusion matrix. For instance, the third row of this table shows that 37, 1, 6, 1 and 2 beat numbers were falsely classified into the N, RBBB, PVC, APB and PB categories, respectively. In this way the number of fusion classifier false negative (FN) detections for the Normal class equals to 47. On the other hand, for instance, the third column of this table illustrates that 21, 0, 5, 0 and 2 beat numbers from the Normal, RBBB, PVC, APB and PB categories were falsely classified as LBBB class, i.e., the number of fusion classifier false positive (FP) detections for the LBBB class equals to 28.

VII. ARRHYTHMIA CLASSIFICATION PERFORMANCE COMPARISON WITH OTHER WORKS

In the final step, in addition to comparison the result of this study with Melgani–Bazi [29] (previous section), the method is assessed relative to other high-performance recent works in order to show the marginal performance improvement of the proposed arrhythmia hybrid classification algorithm. The
In this study, a new supervised heart arrhythmia hybrid (fusion) classification algorithm based on a new QRS complex geometrical features extraction technique as well as an appropriate choice from each beat RR–tachogram was described. In the proposed method, first, the events of the ECG signal were detected and delineated using a robust wavelet–based algorithm. Then, each QRS region and also its corresponding DWT were supposed as virtual images and each of them was divided into eight polar sectors. Next, the curve length of each excerpted segment was calculated and is used as the element of the feature space. To increase the robustness of the result of comparison of the proposed method and other works is shown in table 7.

### TABLE III

<table>
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<th>PB</th>
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### TABLE V

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### TABLE VI

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### VIII. Conclusion

In this study, a new supervised heart arrhythmia hybrid (fusion) classification algorithm based on a new QRS complex geometrical features extraction technique as well as an appropriate choice from each beat RR–tachogram was described. In the proposed method, first, the events of the ECG signal were detected and delineated using a robust wavelet–based algorithm. Then, each QRS region and also its corresponding DWT were supposed as virtual images and each of them was divided into eight polar sectors. Next, the curve length of each excerpted segment was calculated and is used as the element of the feature space. To increase the robustness of...
TABLE VII
APPROXIMATE PERFORMANCE EVALUATION OF THE PRESENTED NEURO–SVM–MLVQ FUSION CLASSIFICATION ALGORITHM WITH A PREVIOUS STUDIES AIMED FOR VALIDATING THE OBTAINED RESULTS AND SHOWING MERIT OF THE METHOD.

<table>
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<th>Authors</th>
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<th>Dataset</th>
<th>Accuracy</th>
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<td></td>
<td></td>
<td></td>
<td>850 training-850 testing;</td>
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<td>(Normal: 800, PVC: 260,</td>
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<td>APB:260, RBBB: 260, F:260)</td>
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<tr>
<td>Mrs. B.Anuradha and V.C.Veer Reddy [45]</td>
<td>Feature extraction;</td>
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<td>Spectral entropy, Poincare plot geometry, Largest Lyapunov exponent and and Detrended fluctuation analysis Classification: antifs</td>
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<td>N.Kannathal and C.M. Lim [36]</td>
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<td>320 training–200testing;</td>
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<td>APB:338, PB:6821)</td>
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APPENDIX A
ABBREVIATIONS
LVQ: learning vector quantization
MLVQ: modified LVQ
KNN: K nearest neighbors
PNN: probabilistic neural networks
SVM: support vector machine
ECG: electrocardiogram
DWT: discrete wavelet transforms
SNR: signal to noise ratio
ANN: artificial neural network
MEN: maximum epochs number
NHLN: number of hidden layer neurons
RBF: radial basis function
MLP-BP: multi-layer perceptron back propagation
LR: learning rate
FP: false positive
FN: false negative
TP: true positive
P+: positive predictivity
Se: sensitivity
MITDB: MIT-BIH arrhythmia database
SMF: smoothing function
FIR: finite-duration impulse response
LBBB: left bundle branch block
RBBB: right bundle branch block
PVC: premature ventricular contraction
APB: atrial premature beat
PB: paced beat
N: normal (rhythm)

REFERENCES


Mohammad Reza Homaeinezhad was born in Shiraz, Iran, in 1980. He received his BSc, MSc and Ph.D. degrees (with the best honors) all in Mechanical Engineering, Dynamic systems and control, in 2003, 2005, 2010, respectively from K. N. Toosi University of Technology, Tehran, Iran. Since September 2010, he has been an assistant professor of Mechanical Engineering (bio-mechatronics) at K. N. Toosi University of Technology and his research interests include nonlinear dynamics and control, statistical signal analysis and parameter estimation, automatic decision making (detection and modulation) theory and biomedical waveforms (ABP, ECG and PCG) processing.

Ehsan Tavakkoli was born in Damavand in 1985. He received the BSc and the MSc degree in Mechanical engineering from Mazandaran University and K.N. Toosi University of technology, respectively in 2008 and 2011. Since 2009 he has been a member of the CardioVascu lar Research Group (CVRG). His research interests include artificial intelligence, signal processing, control and pattern recognition.

Majid Habibi was Born in Tehran, Iran in 1979. He received his B.S. degree in Software engineering from Payame Noor University in 2004. He also received his M.S. degree in Mechatronics engineering in 2011 from K.N. Toosi University of technology.His research interests include artificial intelligence and control.

Abbas Atyabi was born in Golpayegan, Iran in 1986. He received the BSc and the MSc degrees in Mechanical engineering, and Mechatronics engineering from Golpayegan College of Engineering (Joint program with Sharif University of Technology) and Islamic Azad University – South Tehran Branch respectively in 2008 and 2011. Since 2009 he has been a member of the CardioVascular Research Group (CVRG) – K. N. Toosi University of Technology. His research interests include Intelligent Patient Monitoring, Biomedical Image and Signal Processing and machine learning, artificial intelligence and pattern recognition.

Ali Ghaffari was born in Neyshabour in 1947. He received the BSc, MSc and Ph.D. all in Mechanical Engineering from Sharif University of Technology, Georgia Institute of Technology and University of California at Berkeley in 1971, 1974 and 1978, respectively. Since, 1979 he has been with the department of Mechanical Engineering of K. N. Toosi University of Technology. Professor Ghaffaris research is mainly focused on dynamic systems and control including analysis of stochastic phenomena, dynamics and control of nonlinear systems, application of fuzzy set theory and artificial neural networks to mechanical systems, and biomedical signal processing, specifically ECG.