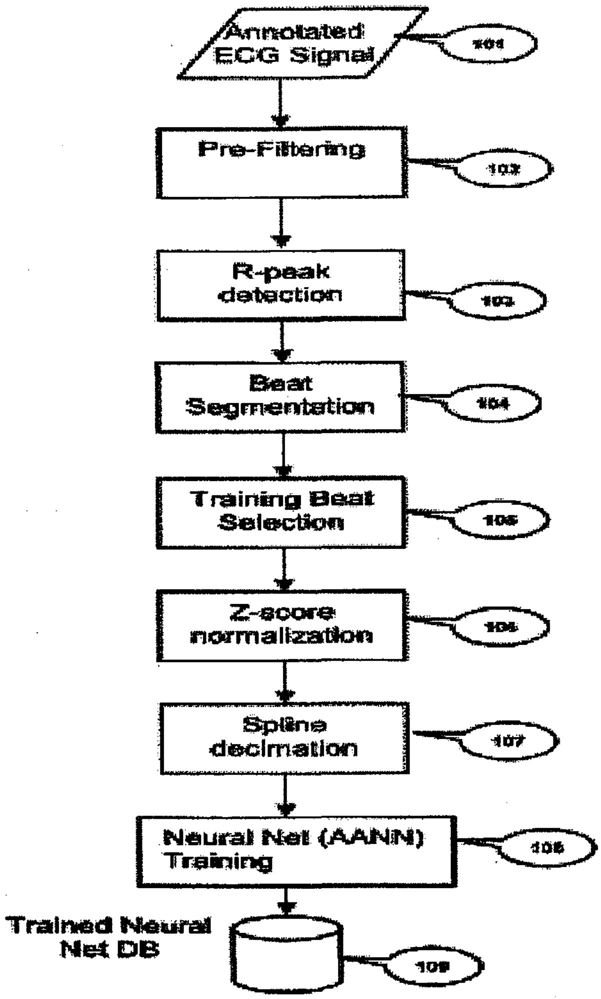

Figure 1

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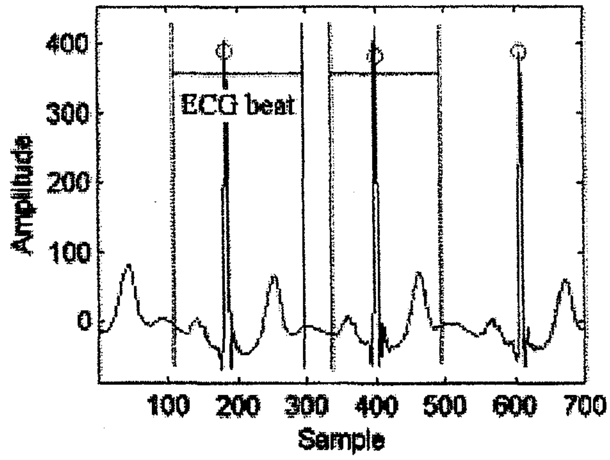

Figure 2A

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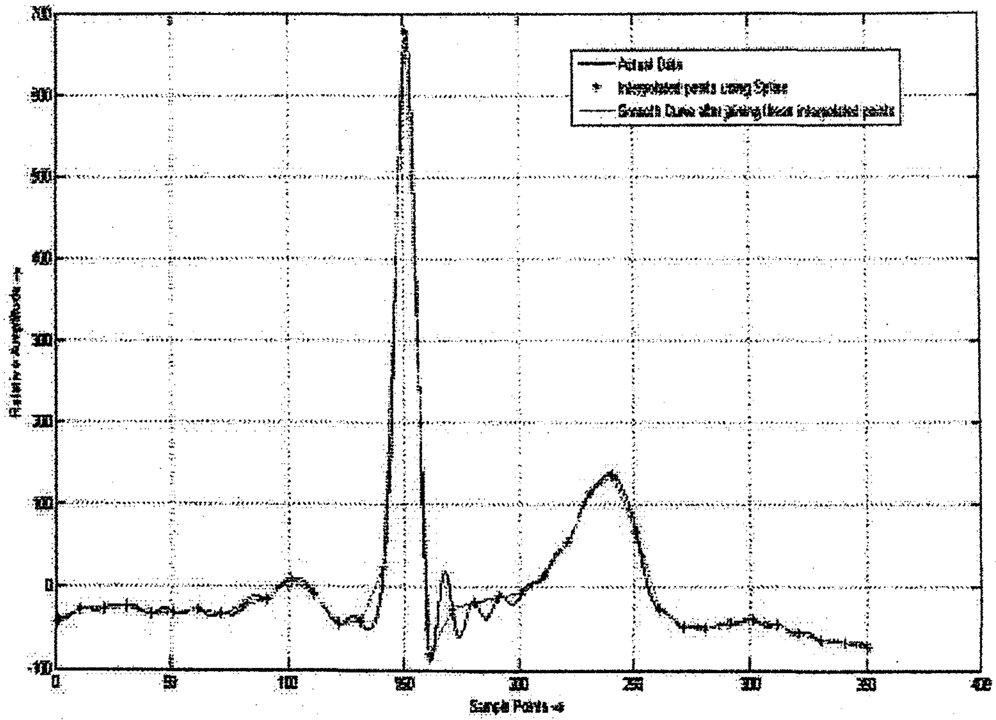

Figure 2B

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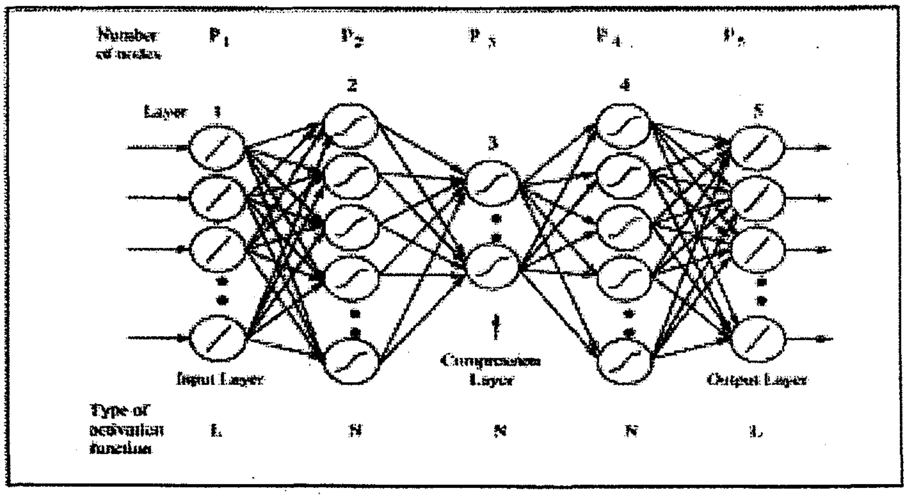

Figure 3

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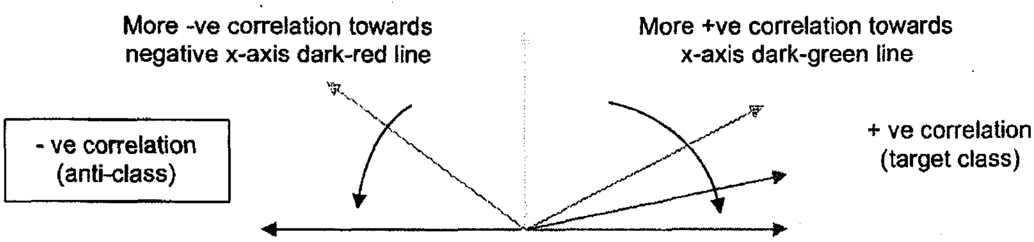

Figure 4

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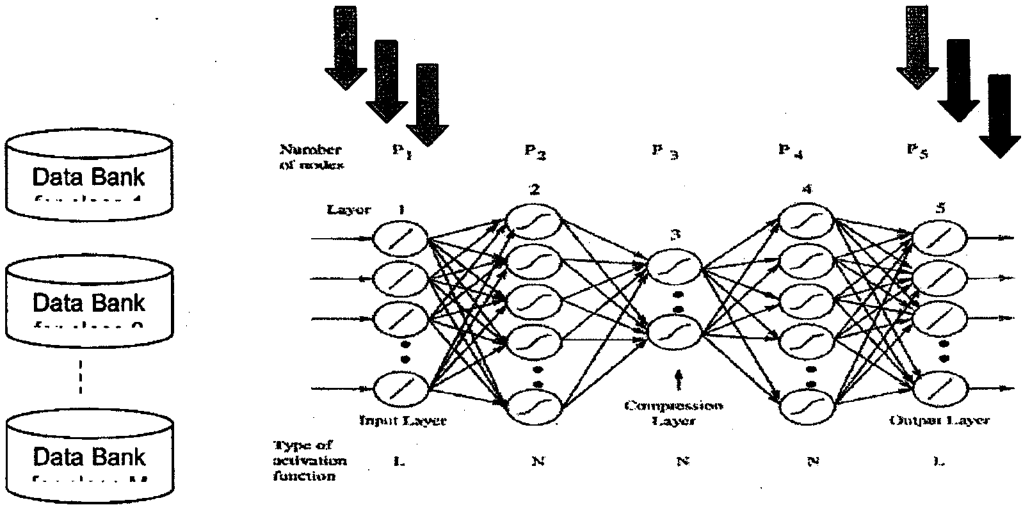

Figure 5

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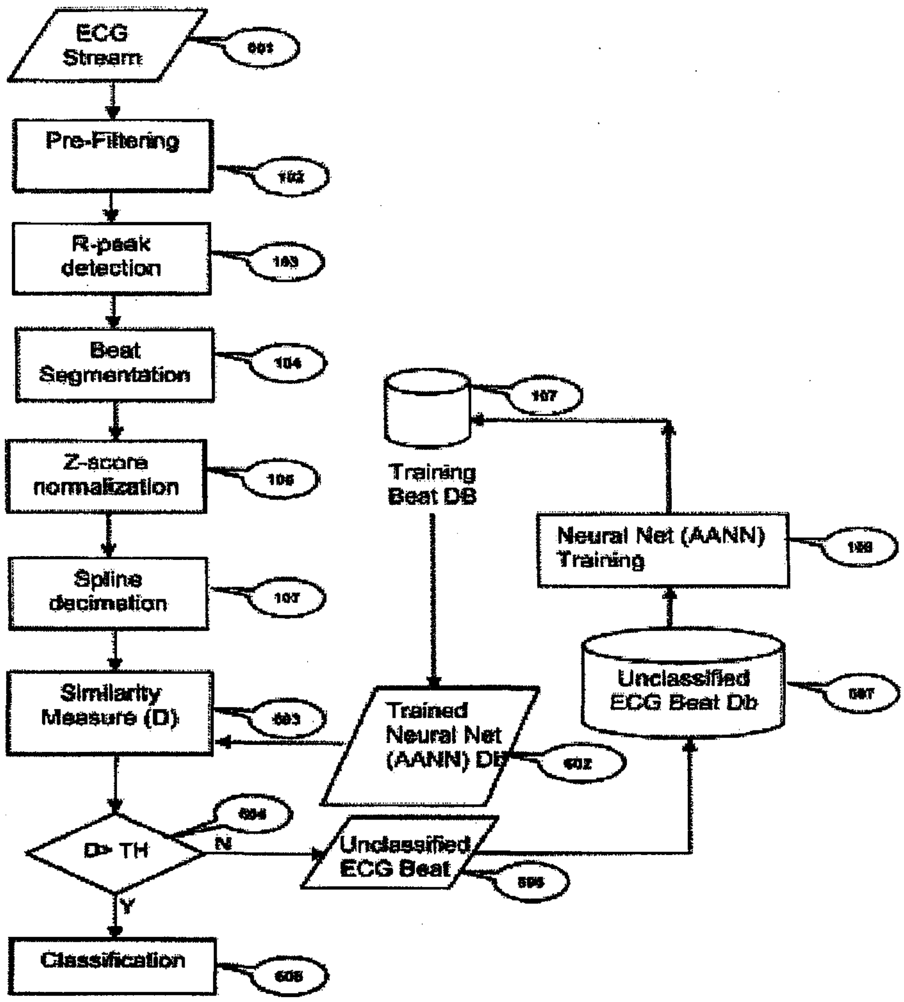

Figure 6

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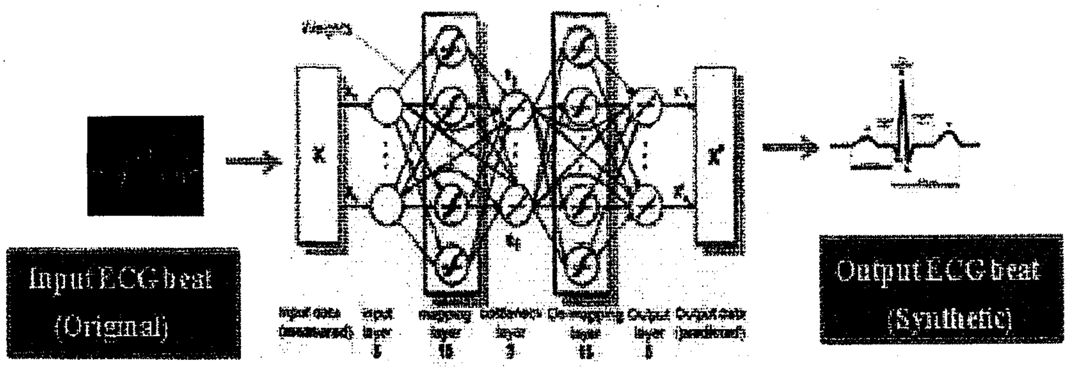

Figure 7

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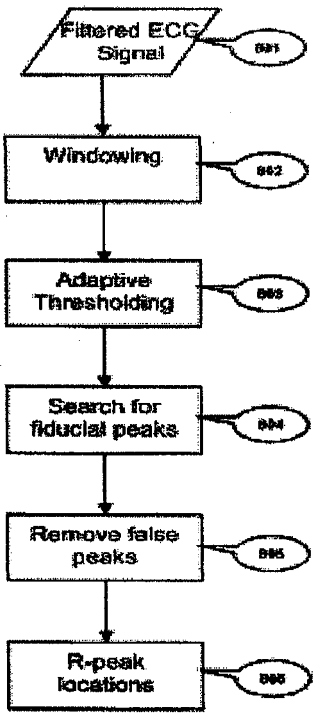

Figure 8

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FIELD OF THE INVENTION

The present invention generally relates to the field of arrhythmia classification devices, and more particularly relates to method and apparatus for classifying arrhythmia using auto-associative neural network and spline based decimation.

BACKGROUND OF THE INVENTION

Automatic detection and classification of ECG patterns is of great value in diagnosis and treatment various cardiac arrhythmia conditions. This is because arrhythmias cause a serious threat to the patients recovering from acute myocardial infarction. Automatic arrhythmia detectors have high impact on the quality of life and prevent the risk of stroke or sudden cardiac death in high-risk cardiac patients. Hence, there is a need for timely and real-time detection of various cardiac arrhythmia conditions.

The cardiac arrhythmia detection and classification problem has been addressed in the literatures in various ways. Sophisticated classification algorithms which give superior accuracy are relatively easy to implement in high end processors. However, such techniques may require high memory and iterative computations which are time consuming. Therefore, the existing techniques cannot be used for real-time applications in mobile devices or hand-held devices (low-end processors). However, real-time implementation of classification algorithms in smart-phone/mobile environments is a requirement for early detection of arrhythmia in telemedicine scenario.

BRIEF DESRIPTION OF THE ACCOMPANYING DRAWINGS

Figure 1 is a process flowchart illustrating an exemplary method of creating a training beat database, according to one embodiment.

Figure 2A is a schematic representation illustrating selection of Electro-cardiogram (ECG) beats representing one cardiac cycle by moving backward and forward of R-peak.

Figure 2B is a schematic representation illustrating a comparison of actual data, the beat approximation through Auto Associative Neural Network (AANN), and interpolation of an ECG signal using spline interpolation technique.

Figure 3 is a schematic representation illustrating an Auto Associative Neural Network (AANN) model.

Figure 4 is a schematic representation illustrating a correction principle for discriminating training.

Figure 5 is a schematic representation illustrating a discriminating training method for the AANN model.

Figure 6 is a process flowchart illustrating an exemplary method of classification of arrhythmia, according to one embodiment.

Figure 7 is a schematic representation illustrating generation of synthetic beat by applying AANN.

Figure 8 is a process flowchart illustrating an exemplary method of detection of R-peak in an ECG signal, according to one embodiment.

BRIEF DESCRIPTION OF THE INVENTION

The present invention provides a method and apparatus for

Figure 1 is a process flowchart 100 illustrating an exemplary method of creating a training beat database, according to one embodiment. At step 101, an annotated ECG signal is inputted. At step 102, the annotated ECG signal is filtered using a band pass filter of 0.5-40Hz. The band pass filter includes a high-pass filter having cut-off frequency 0.5 Hz to remove low-frequency base-line wanderings and low-pass filter having cut-off frequency 40 Hz.

At step 103, an R-peak in the filtered ECG signal is detected and the location of R-peak corresponding to each beat is outputted. R-peak/wave is one of the most prominent peaks in an ECG signal and has been considered as upward defection in QRS complex. At step 104, the region of a beat is segmented based on the detected R-peaks.

At step 105, ECG beats representing entire one cardiac cycle is selected by moving backward and forward of R-peak as shown in **Figure 2A**. From an ECG signal, 351 sample points (R-150 to R+200, 0.41 sec backward and 0.55 sec forward of R peak, for 360 Hz sampling frequency of ECG record) that represents one full cardiac cycle are selected. Since each beat has contained same number of samples, the time axis is not normalised. Equal number of samples (351) is chosen from each of the beats to facilitate similarity measure to operate on unknown incoming beat and the beat in the database.

The candidate training beats includes Normal (N), Left bundle brunch block (LBBB), Right bundle brunch block (RBBB), Premature ventricular contraction (PVC), and Atrial premature contraction (APC) classes for arrhythmia classification.

At step 106, a raw ECG beat is normalised using z-score normalization to meet zero mean and unity variance.

$$x_{norm} = \frac{x-\mu}{\sigma} \ldots\ldots(1)$$

where, x, x_{norm} μ and σ are original signal, normalized signal, mean and variance respectively. It can be noted that normalization is applied both in training and testing phases.

At step 107, spline interpolation operation, which returns a set of polynomials and from those polynomials, interpolation is performed (both at training and testing phases) to obtain reduced number of points representing the normalized signal. A spline is a sufficiently smooth polynomial function that is piecewise-defined, and possesses a high degree of smoothness at the places where the polynomial pieces connect (which are known as knots). Spline is widely used where the shape of the signal needs to be preserved as shown in **Figure 2B**. Note that the coefficients of functions/polynomials have been stored instead of samples during training phase and desired numbers of samples (e.g., 32) are calculated from those polynomials at the time of test. Spline interpolated polynomials are expected to reproduce the accurate sample point based on the query. This would help identify knots in an ECG beat using the interpolation technique and accordingly capture a signal's shape. Spline is known for piecewise polynomial approximation of signal which could preserve shape information of a signal. The present invention helps reduce sample effectively and choose the points which is the most valuable (like breaks, knots and these points can describe the section very well) point in the sub-division of the signal.

At step 108, the neural network training algorithm (e.g., back propagation) in the feed-forward Neural Network is run on incoming ECG beats from same pattern class. Back propagation algorithm starts from the output node and propagate error through several hidden nodes back to the input for updating the weights. In each iteration (Batch mode), the sum of errors reduces ensuring learning and more optimized weight. Training stops when number of iterations crosses its limits or rate of change of error (from earlier iteration) is not significant. At step 109, the database of weights (after training) of all trained neural networks is formed.

In an example, Auto associative neural network (AANN) is used as a feed forward neural network model that performs identity mapping. An exemplary AANN model is shown in **Figure 3**. After training, the AANN model reproduces the input vector (e.g., Synthetic beat) at the output with minimum error if the input is from the same system. The neural network is expected to capture the morphological information present in the higher order relations among the samples of an ECG beat. The AANN model consists of one input layer, one output layer, and one or more hidden layers. For one set of the experiments, ***351L-20NL-20L-20NL-351L*** *are used*, where *NL* signifies non-linearity (Tanh activation function) whereas *L* is denotes linear nodes to accommodate complete length of training beats. In another set of experiments, each beat is reduced by Spline operation from 351 samples to 32 first and then reduced beat (of 32 dimensions) is inputted to AANN. The AANN structure for this is would be ***32L-20NL-20L-20NL-32L***. Each beat after z-score normalized is inputted in AANN in both inputs as well in output. Weights are optimized (updated) using the adopted training algorithm (back propagation) for more beats belonging to same pattern class.

Discriminative training scheme as shown in **Figure 5** is used to achieve more separation among pattern classes. Like normal training procedure, discriminative training starts with a copy of input data to output for the target class. Then, for anti-class (Classes other than target class), negative version of input data is presented to the output for achieving discrimination. The notion of presenting the negative version of data is to exploit negative auto correlation of ECG beats from anti-classes. In **Figure 4**, ECG beat vector is shown by arrow. When the same ECG beat is presented in input and output stages of ANNN for target class, the auto correlation between the two input beats is maximum (i.e., the correlation is +1) and the inputted beats are perfectly aligned with each other. Contrary to this, for anti-class, the copied version of input is negated and presented to output layer of ANNN so that there would be 180 degree phase shift (The correlation is -1) between them (in **Figure 4**, between green and red input vectors; correlation is -1). In any cases (either in non-discriminative or discriminative), weights of AANN are stored instead of beats to represent the pattern class.

Figure 6 is a process flowchart illustrating an exemplary method of classification of Arrhythmic beat, according to one embodiment. At step 601, an ECG signal is inputted for test. It can be noted that, the steps 102, 103, 104 are applied for classification of Arrhythmic beat for the same purpose as in **Figure 1**. At step

602, Neural Networks is selected from a database of weights of all trained neural networks for similarity measure.

At step 603, similarity measure is performed. In one embodiment, each test beat (query) is inputted to all Neural networks beats (in Neural Network database) from different arrhythmia classes and a similarity measure is computed between query beat/reduced query beat and a beat generated from the output of the neural network using sum square difference. **Figure 7** is a schematic representation illustrating the way, which AANN model is used to generate synthetic beat. The similarity score can be determined using sum of square of difference between input ECG and its synthetic ECG beat (Or in reduced domain when spline interpolation has been used) from AANN output.

$$D = \sum_{k=0}^{DataLength-1} \left(ECGBeat_{input}(k) - ECGBeat_{output}(k)\right)^2 \ldots\ldots(2)$$

At step 604, it is determined whether highest similarity measure (D) (Minimum score) between all the training beats is within certain threshold (TH). If D>TH, then the step 605 is performed, else step 606 is performed.

At step 605, the beat is selected as unclassified beat for which the highest similarity measure (D) is higher than the threshold (TH). At step 607, the unclassified beat is updated as a new class for a new training database called "Unclassified ECG Beat db". The Unclassified ECG Beat db is a database of unclassified beats for the current experiment, and for which the same Neural Network training could be adopted. In some exemplary implementations, the definition of the class can be assigned with the consultation of medical expert. If D<TH, then at step 606, the label of reference class corresponding to the highest similarity measure (lowest D) is assigned to the test beat.

Figure 8 is a process flowchart illustrating an exemplary method of detecting R-peaks in an ECG signal, according to one embodiment. At step 801, an ECG Signal is inputted for R-peak detection. At step 802, the ECG signal is windowed for adaptive threshold determination and peak detection. Let the original ECG signal be denoted by $x_0[n]$ and the ECG signal is assumed to be sampled with sampling frequency Fs Hz. In order to determine the threshold, the window size is chosen to be T=2 seconds and the value is based on the assumption that the slowest acceptable heart rate is 30 BPM which corresponds to one beat in 2 seconds. Moreover, to account for situations where only a portion of a peak is captured by a given window, adjacent windows are overlapped by a factor T_0 (e.g., 0.61 seconds).

At step 803, a threshold is computed based on the absolute difference signal for the window. An ECG signal ($x_0[n]$) is then passed through an absolute differentiator to obtain $x_1[n]$ as in (3). Threshold (Th) is calculated using equation (4).

$$x_1[n] = |x_0[n] - x_0[n+2]| \qquad \ldots\ldots. (3)$$

$$Th = \tau * x_1[n] \qquad \ldots\ldots. (4)$$

The differentiator acts as combination of an averaging filter and a high pass filter which suppresses the effect of intermediate variance. The z-transform of the filter is as follows:

$$x_1(z) = (1\text{-}z^{-2})\, x_0(z) \qquad \ldots\ldots. (5)$$

where x_0 (z) and $x_1(z)$ are the z-transforms of original and filtered signal. This can be realized using two filters as the following:

$$x_{01}(z) = (1+z^{-1})\,(1\text{-}z^{-1})\, x_0(z) \qquad \ldots\ldots. (6)$$

which leads to one scaled averaging filter as $x_{avg}[n] = x_0[n] + x_0[n+1]$ and a high pass filter $x_{hp}[n] = x_{avg}[n]\text{-}x_{avg}[n+1]$.

The differentiator calculates the slope between two samples separated by a single sample. This operation suppresses the effect of an intermediate variance. The absolute differentiated value is taken because; the magnitude of the slope is to be determined. Particularly, steep slope characteristics of a QRS complex are used for R-peak detection.

At step 804, the fiducial peaks are searched within the window. R-peak is detected based on Threshold supplied from the earlier stage. The threshold is used to discard other peaks like P or T of the ECG signal. The slope of the QRS is much higher than the slope of P or T waves. Therefore, the slope of the portion which is above the threshold should indicate the presence of the QRS complex. In order to detect the R-peak, the samples are fiducially marked wherever $x_1[n]$ crosses Threshold. Then, the maximum value is searched within MAX_SR_WIN (chosen to be 0.2 sec.) of the ECG sample $x_0[n]$, starting from fiducial marks (loc). Effectively, the maximum value is the fiducial R-peak of that QRS. Once the R-peak is detected, there may not be more QRS within certain acceptable time namely, SKIP_WIN (0.25 sec.) and hence all the fiducial marks which come within SKIP_WIN are discarded. The computation in searching the peak is thus reduced significantly by discarding the fiducial points within the SKIP_WIN.

At step 805, false peaks are removed. Due to the overlapping window, there can be two possibilities of false detection a) the same peak is detected twice, and b) the peak straddles the boundary of the window and as a result the location of the maximum obtained by the method corresponds only to the maximum within the window and not the actual maximum of the peak. To evade false detection, the location of the two consecutive detected peaks is calculated. If the difference is less than the SKIP_WINDOW (as there should not be two peaks detected within this limit), the location with minimum amplitude is discarded and the location of the maximum amplitude is declared as a peak. In order to find the exact location of the R-peak for long ECG data, the location of R-peak has to be adjusted with the offset of the overlapped window. At step 806, the true R-peak locations detected.

Dated this the 28th day of January 2013

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ABSTRACT

The present invention provides a method and apparatus for classifying arrhythmia using discriminative auto associative neural network and spline based decimation. According to the present invention, an ECG signal is inputted for test. Then, auto-associative neural networks are selected from a neural network database. Further, each test beat (query) is inputted to all Neural networks beats in Neural Network database) from different arrhythmia classes and a similarity measure is computed between query beat/reduced query beat and a beat generated from the output of the neural network. Furthermore, it is determined whether highest similarity measure (D) between all the training beats is within a certain threshold (TH). If D>TH, then the beat is selected as unclassified beat and the unclassified beat is updated as a new class for a new training database. If D<TH, label of reference class corresponding to the highest similarity measure is assigned to the test beat.

Figure 6