SMART HELMET: WEARABLE MULTICHANNEL ECG & EEG

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Abstract

Nowadays many modern wearable devices have been introduced for monitoring the health. A helmet is proposed for monitoring the activities like cardiac activities .Here the helmet make use of sensors or electrodes for monitoring the cardiac activities and the vital signs of the body. The electrodes are embedded with the face-lead positions that embedded within the helmet. The electrodes are placed at the multiple positions such as lower jaw, mastoids, forehead. A respiration belt around the thorax and a reference ECG from the chest serve as ground truth to assess the performance. Walking and cycling were used for the real-time scenario. A multivariate R-peak detection algorithm is proposed for the noisy environment.

Keywords: Multichannel R-peak detection, QRs complex, wearable ECG

Introduction

The monitoring recording devices are becoming prerequisite for the assessment of the state of body. wearable devices are more contaminated by the noise due to the subjects movement compared to the stationary recording. This artefacts are generated due to muscle contraction. The smart helmet is introduced specially for people who does the racing and also for the soldiers who ll be busy with their schedule so much that they wont be having time to look after their health. The smart helmet is embedded with the dry electrodes that record the cardiac activities of person. A number of life threatening injuries are occurring during bike racing, cycling and car racing which has motivated to introduce the smart helmet. Using smart helmet many accidents and uncertainties can be avoided.

RELATED WORK

R-PEAK DETECTION IN ECG

The ECG recorded from the wearable devices requires robust signal processing techniques for artifact removal. For identifying the R-peak in the noisy environment a standard approach like match filtering has become the common approach. But it is necessary to find the QRS pattern and identify the similar pattern.QRS pattern can be identified by many approaches.

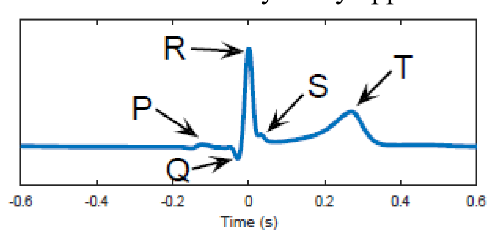

Fig. 1:The ECG-cycle with its most significant features and labels

A. Pan & Tompkins algorithm

The basis of this algorithm is slope, amplitude and width of the signal. There are two different stages in this algorithm [1] (a).Pre-processing (b).Decision.

Pre-processing: In this stage, the signal is passed through a block of filters to reduce noise and the influence of T-wave. The block of filters is a combination of low-pass and high-pass filters. Low-pass filter is used to remove noise whereas high-pass filter is used to reduce the influence of T-wave.

Next step is to apply the derivative to the output obtained from the filter. This provides complex slope information.

The slope is then intensified by squaring the signal point by point. This also helps in reducing false positives.

Final step is to apply a moving window integrator which includes information about slope and width of the signal. This integration window contains the QRS complex.

Decision: In this stage, the signal is ready for QRS detection. Two sets of thresholds are applied to both the derivative signal and the moving window integration signal. Marks are considered in both signal and then only the mark where the peaks coincide in both signals is considered as QRS complexes.

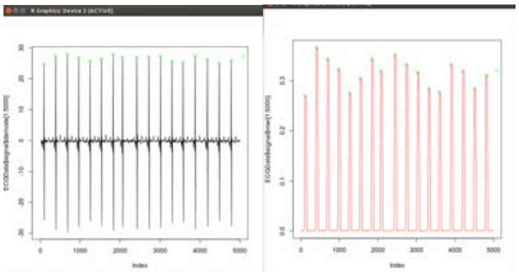

Fig. 2:(a)R peaks detected in the derivative signal.(b)R peaks detected in the mwi signal

B. Neural-Network Based QRS Detection

Artificial neural networks have been are used for nonlinear signal processing, and optimization.[4]To model the lower frequency of ECG the ANN used adaptive whitening filter for non-linear and no stationary. Here the hidden layer with nonlinear unit is added to model more complicated nonlinear signal.

a. Neural-Network-Based Nonlinear Whitening Filter

This approach deals with the nonlinear ECG signal that is replaced with the linear adaptive whitening filter. In this linear adaptive filter is derived by adding nonlinear hidden layer with nonlinear processing unit [2]t. Each of the hidden units produces a.nonlinear intermediate result

$$z_i=f(^{M}\sum_{i=1} w_{ij} y_{t-1}+bj)$$

where f( ) is a sigmoid function defined as

$$f(x) = \frac{1}{1+e^{-x/T}}$$

The value of T, called temperature, controls the nonlinearity of the function. The smaller the value of T, the more nonlinear the function.

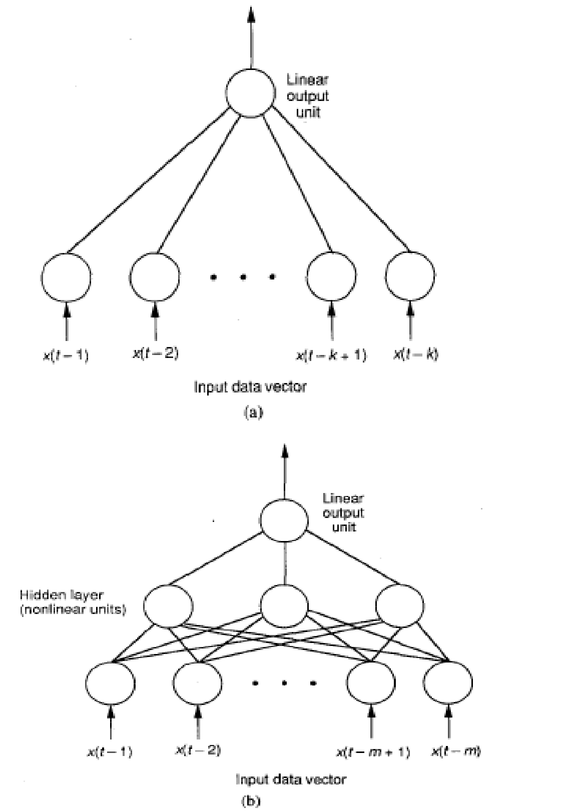

Fig. 3:Adaptive filter structure.(a)Single-layer linear.(b)multilayer nonlinear.

The template that is filtered by the adaptive whitening filter with the filtering of the input signal. The whitened QRS template given as

$$WQRS(t)_k ORS(t)_k - \sum_i{}^{a}{}_{=1} u_i \int(\sum_{j=1}^{M} w_{ij} QRS(t)_{k-j}+b_j)$$

Where k = 1,... , L - M; L is the length of the QRS template vector; and **M** is the number of input units in the model.

b. Neural-Network-Based Ad aptive Matched Filtering

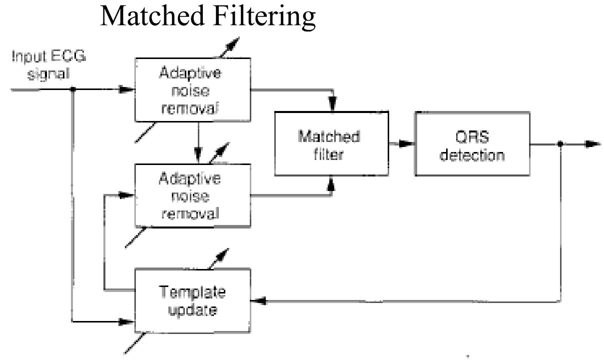

Fig. 4:Block diagram of ANN-based adaptive matched filter for detection of QRS complexes in an ECG signal.

The ECG signal is used as a input that is sent through the adaptive whitening filter that is used as a part of the neural net based nonlinear adaptive noise removal filter.The input layer gets the data vector from ECG signal ,input pattern is used as a data vector and the target pattern is yr.

$$Y(t-1)=\{y_{1-q},y_{t-q+1},\ldots,y_{t-1}\}^T$$

By shifting the time window one step forward the input and the target pattern are updated. If the original signal is approximately stationary, the weights will not change much after they have converged to certain values, which approximate the local minima on an error surface..When the new QRS complex is identified the template bank is updated or else it remains unchanged. The averaged template is filtered by the same adaptive noise removal filter from the neural net model synchronously with the signal filtering process. The output of the template filter forms a matched filter which filters the output of the data whitening filter. Finally, the data output from the matched filter is sent to the QRS detection circuit, which includes squaring, moving averaging, and threshold checking.

C. R-Peak detection combining matched Filtering And Hilbert Transform

Due to the low resolution sensors the ECG data are contaminated by noise, motion artifacts . These affects the quality of the R-peak data and can lead to the misinterpretation of the state of the body like monitoring the stress .The combination of the matched filtering and Hilbert transform was introduced for the R-peak detection. Here the RR intervals and cross-correlation are used in conjunction to automatically locate the R-peaks and also to display the ambiguous peaks using interactive graphical user interface [3].

Matched filtering

The matched filtering start from the defined waveform or function to search similar pattern in the time series and this can be performed by taking the convolution between the conjugate of the defined mother pattern h(k) and the original signal x(n) with length N.

$$Y(k)=\sum_{k=1}^{N-k}h(k)x(n-k)$$

This results the high amplitude at the time when time series that resembles the mother pattern or else gives the low amplitude.

b.Hilbert transform.

Hilbert transform use the fourier transform to decompose the signal into frequency.x(t) is the real function and $x^h(t)$ is the complex output of the transform.By using the fourier transform, it results in a π/2 phase-lead for a negative frequency and a π/2 phase-lag for a positive frequency,and computing its magnitude|s(t)| results in a positive envelop of the ECG data which is convenient to locate the R-peak within a specific time window.

$$S(t)=x(t)+jx^h(t)$$

$$|s(t)|=\sqrt{x^2(t)+x^{(h)2}(t)}$$

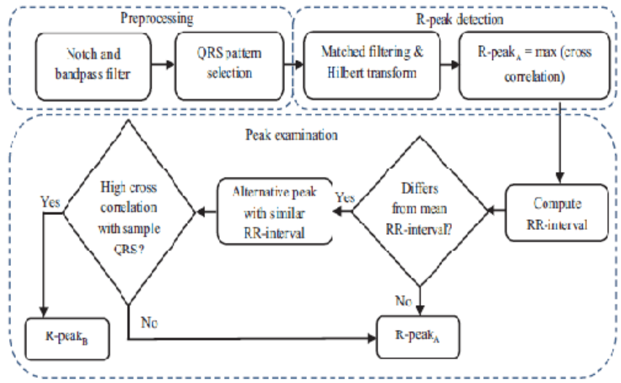

Fig. 5:The MF-HT algorithm of three parts: Preprocessing, R-peak detection and R-peak examination

D.*K*-Nearest Neighbor algorithm (KNN)

The KNN algorithms used for classifying objects that are based on closest training examples in the feature space.

It is also called as lazy learning [5].The KNN algorithm is evaluated in two phases. Training phase and classification In training phase, the training examples are vectors that are there in multidimensional feature space. The feature vectors and class labels of training samples are stored. In the classification phase, *K* is a user-defined constant, a query or test point is classified by assigning a label, which is the most recurrent among the *K* training samples nearest to that query point. In other words, the KNN method compares the query point or an input feature vector with a library of reference vectors, and the query point is labeled with the nearest class of library feature vector. This way of categorizing query points based on their distance to points in a training data set is a simple, yet an effective way of classifying new points.

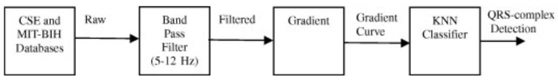

Fig. 6: Schematic representation of intermediate steps for KNN algorithm implementation

MIT-BIH Arrhythmia database is considered for the validation of this algorithm. In preprocessing phase raw digital ECG signal are recorded by the disturbance such as muscle noise. This signal is then sent to the bandpass filter to reduce the muscle noise. A low pass filter is designed with a cut-off frequency of 11 Hz. The design of the high pass filter is based on subtracting the output of a first-order low pass filter from an all pass filter. The low cut-off frequency of the filter is about 5 Hz. The gradient is a vector, has both direction and units, that points in the direction of the greatest rate of increase of the scalar field, and whose magnitude is the greatest rate of change. Finally KNN classifier is used where the k distance metric is found and then the QRS complex is detected.

II. REVIEW

R-peak can be identified by matched filtering and using the multichannel.The artefacts that are present in the signals have similar amplitudes like R-peak. So it is difficult to identify the R-peak in presence of artefacts. When we consider the single channel it will consist many artefacts so we are considering multiple channel it consist of very less artefacts .This artefacts are caused due to the strong mechanical impact to the helmet that would temporarily disturb all the electrodes.

The signals that are received from the electrodes are contaminated with the are passed through the high pass filter of cut-off frequency 2Hz,so all the frequency below the 2Hz are blocked Then the cross-correlation with the QRS pattern will be calculated. Cross-correlation is used to find the match between two signals. Then in R-peak prediction. Starting from the last detected R-peak, the TW window is multiplied with the signal to extract the signal between two R-peaks. The width of the window is taken as $2*RR_e$, where $RR_e$is the mean of seven most recent RRI – RR Interval. Next step is the R peak detection. R-peak is found by calculating the maximum for each channels individually after applying a weighting window. The above three steps are applied individually to every channels. Next step is Multichannel R-peak detection containing the following sub steps.Mark a maximum in channels with trapezium.

Sum the trapezium over all channels.Identify the peak in the sum.The peak detected using this workflow is use as the reference (starting point) for next iteration.

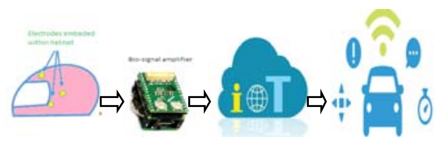

Fig. 8: Data Processing

The helmet embedded with electrodes senses the signal and send it to the bio-signal amplifier where the analog signals are converted into digital signal and then the dat is written on the cloud and from there the data is accessed .For example if the person is doing a car racing and suddenly he is getting a cardiac arrest he won't be in the position to put break to his car as he will be in full speed at that particular time the smart helmet that he is wearing will sense the signals and it will send those signals to bio-sinal amplifier then the amplifier will send automatically slows down and then put the break.

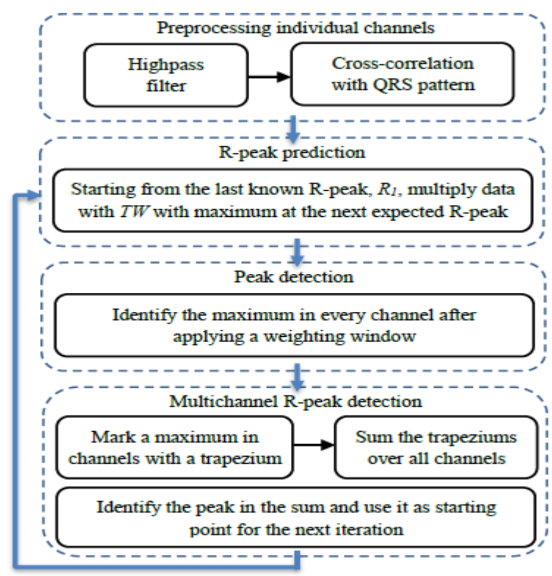

Fig. 7:R-peak prediction and multichannel R-peak detection algorithm

III. CONCLUSION

The demonstration of the smart helmet in which the electrodes mounted inside the helmet can reliably record cardiac and neural activities.To deal with such noisy real-world scenarios, developed a signal processing approach based on matched-filtering and an adaptive weighting function for R-peak prediction across multiple channels. This has resulted in values for the sensitivity and positive predictivity parameters close to 100% and 90%.

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