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Quality Assessment of 12-Lead ECG in Body Sensor Network

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Abstract: Body sensor network (BSN) is simple and effective biophysical data capture in real time to monitor human activities, such as health status and physiological signals for a wide range of application area. Electrocardiogram (ECG) uses medical body sensors to record the electrical activity of the heart to help diagnose of heart disease, and also monitor how well different heart medications are working. ECG is usually by affected by various types of noises. The most common noises originated from the power line interference, electrodes loss contact, baselines wander and motion artifact. This paper introduces a new technique for improving the quality of ECG using multi scale quantitive recurrence analysis (QRA) for feature extraction and decision tree classifier. Our approach achieved classification accuracy of 98.32% on set A training set and 92.4% on set B testing set without label from the Computing in cardiology/PhysioNet Challenge 2011 dataset.

Keywords: BSN, ECG, QRA, Decision tree.

1. INTRODUCTION

Body Sensor Network (BSN) is a network of sensors attached to human bodies [1, 2]. These body sensors continuously monitor patients' physiological data, and transmit sensed data to doctor's site for real time diagnosis. One of the most popular healthcare measurements in BSN is electrocardiogram (ECG). The electrocardiogram ECG is the main tool to examine the heart diseases. The ECG is characterized by a series of waves that are obtained by placing electrodes on the chest, arms, and legs to provide information of the electrical activity of the heart.

In many situations, the recorded ECG signal is often corrupted by different types of noises and artifacts, such as baseline wander, loose electrode connection, and motion artifact [3]. Hence when this record is received by the physician, it may cause wrong diagnosis due to degrade diagnostic information or maybe it needs more effort from the physician. Therefore the quality assessment is an essential issue for improving the quality of ECG signals by eliminating the corrupted ECG record before delivering it to the physician.

Although relatively number of researchers have been published on PhysioNet 2011 challenge of ECG signal quality assessment [4], the topic is still important to review deeply the previous researches and demonstrate how we can increase the performance. The proposed method in this work introduces a set of procedures that used to enhance the quality of ECG signals. The objective of this study is to develop a new combination of feature extraction and classification algorithm that can effectively deal with multi-scale recurrence feature to increase the performance of the evaluation of the quality of ECG records.

The structure of this paper is organized as follow: In Section 2, the related works will be introduced. The proposed method will be covered in section 3. The simulation result and discussion are given in section 4. Conclusion is given in section 5.

2. Related Work

Although relatively number of researchers have been published on PhysioNet 2011 challenge of ECG signal quality assessment [4], the topic is still important to review deeply the previous researches and demonstrate how we can increase the performance. In [5] authors develop twelve signal quality heuristics called the matrix of regularity. The elements were then summed and thresholded to provide a classification for a given 12 lead ECG [5]. In [6] authors use the quantitive recurrence analysis with self- organization map classifier. In [7] authors explore series of steps of statistical and spectral characteristics for extraction feature with decision tree classifier. In [8] authors use a series of signal quality metrics (based on morphological, statistical and spectral characteristics) and a support vector machine or multilayer perceptron neural network. In [9] authors use decision support system to identify movement artifact, QRS locations and signal quality. The template-based and signal morphology-based features were then presented to a Parzen-window supervised statistical classifier model. In [10] use the four criteria; a no signal detector, a spike detector, a

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lead crossing point analysis and a measure of QRS detection for assist the quality of ECG signal. In [12] adjust threshold system to identify four major sources of ECG quality disruption. In [13] describe two step algorithms: first identifying missing signals, large voltage shifts, and saturation, then quantifying baseline, bowerline, and muscle noise using average template matching. In [14] authors identify baseline drift, flat line, QRS- artifact, spurious spikes, amplitude step changes, and other noise, using a time frequency approach. Classification was based on cascaded single-condition decision rules tested levels of contaminants against classification thresholds. The researches that shown previously are responding to challenge to developed algorithms for classifying ECGs with respect to quality of ECG signals.

3. PROPOSED METHOD

This method is Based on [6] authors' work which is previously addressed in related work; we have modified their work by applying decision tree classifier instead of self-organization map to enhance the accuracy. As shown in figure 1, our architecture is organized as follows - first we describe the noise reduction technique that used to remove most noises in the ECG recodes. Then the multi scale recurrence analysis which is derived 3-lead VCG from 12-lead ECG by dower transformation [15], and integrate wavelet packet [15] with nonlinear and non-stationary methodology as quantitive recurrence analysis to quantify recurrence feature [16, 17]. Finally the decision tree classifier in general and specify its deployment in our algorithm. as illustrated in Fig.1

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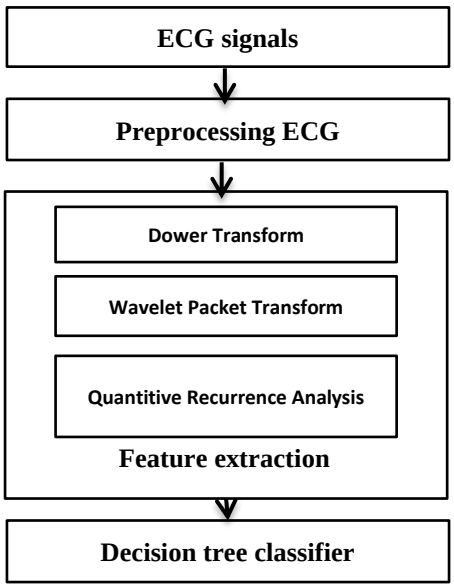

Figure 1: system architecture.

3.1. Signal pre-processing

In fact, it is noted that the noises affect the quality of the signal, especially when non-expert tried to measure the ECG by using mobility device. Additionally, some noises and artifact will impact to ECG signal because of motion artifact, loss contact or misplaced electrode, baseline winder, and power line. The following procedure will be applied on ECG samples by removing most of noises to enhance the quality of ECG. The first step normalize each lead in every sample from [0 to 1], and then filtered each records by using band pass filter between [1 120] at order five, as long as it will remove the baseline wander and high frequencies. The second step eliminates 1s from beginning of each lead in all samples, and another 1s from the end. The third step checks the loose contact of electrodes that appeared as straight line, the straight line is defined by selecting the first order of derivative. Finally, the all samples that have the set of preprocessed operation are filtered, and their size is recognized as: 769 set of acceptable class, 92 of unacceptable class, and 428 from test B.
The remaining data in sets A and B will be used in the following processes of transformation, feature extraction and classification.

3.1. Dower transformation

ECG signal has 12 leads in each sample, these leads (I, II, III, aVR, aVL, aVF, V1,V2,V3, V4,V5, V6) represent the different direction of heart, but some of those leads (III, avR, avL and avF) can be discarded because they are calculated from others. After that the data will be ready to apply inverse dower transform to transform eight leads of ECG of each sample to three-leads VCG as follows:

$$VCG = D_{inv} \times ECG$$

where D_{inv} is the inverse dower transformation matrix (3 × 8) [13] and given by

$$D_{inv} = \begin{bmatrix} -0.172 & -0.074 & 0.122 & 0.231 & 0.239 & 0.194 & 0.156 & -0.010 \\ 0.057 & -0.019 & -0.106 & -0.022 & 0.041 & 0.048 & -0.227 & 0.887 \\ -0.229 & -0.310 & -0.246 & -0.063 & 0.055 & 0.108 & 0.022 & 0.102 \end{bmatrix}$$

ECG is an 8 x m matrix which consists of eight leads (V1, V2, V3, V4, V5, V6, I, and II) from the 12-leads ECG sample, VCG is a 3 x m matrix of XYZ leads and m is the length of ECG recordings.

3.3. Multi-scale recurrence analysis

In this paper, we proposed methods based on Wavelet packet transform (WPT). WPT is a wavelet function that decomposes the signal into approximations and details information, i.e. original signal X noted as W0, then, the approximation coefficient W1,0 is divided into new approximation W2,0 and detail coefficient W2,1. As well as, detail coefficient W1,1 is divided into new approximation W2,2 and detail

coefficient W2,3 [15].

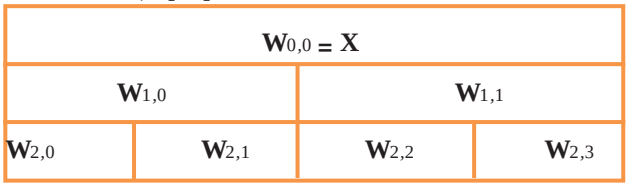

Figure 2: Wavelet Packet Decomposition

This process is decomposed iteratively producing a set of approximation coefficients and detailed coefficient at different levels (N) of decomposition $W_{N,L}$ n=0, 1, …,2N-1, and each sub-signal length is equal m/2N.
After that, the decomposed wavelet sub-signals will be collect the same Scale from different lead of VCG to attractor_i (i=1, 2... 2k). Each attractor has one scale from different VCG lead; consequently it will be used to extract the recurrence patterns. For more details will show in below figure 3.

Quantitive recurrence analysis QRA is a signal analysis methodology able to work with nonlinear and non-stationary system. Moreover, QRA quantify the presence of patterns as parallel line of RP in frequency scales [15].

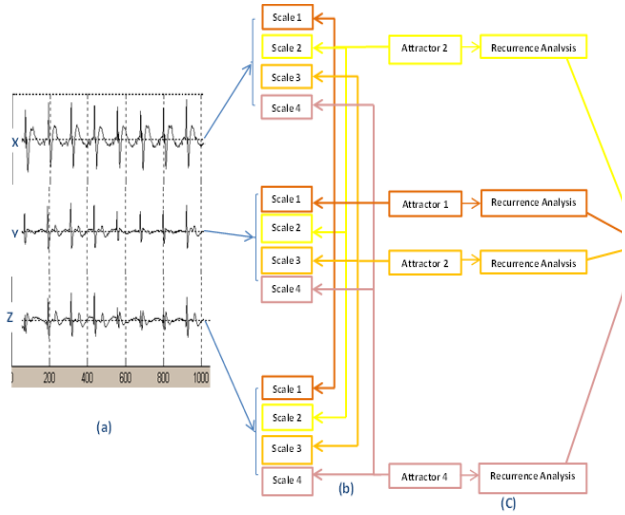

Figure 3: (a) the output from dower transform (b) wavelet packet (c) QRA (d)feature extraction

The Recurrence Plot is graphical tool based on phase space to captures relationships existing in the transformed 3-lead VCG vector space. Therefore, The Threshold Recurrence Plot can be presented as: $TRP_{i,j} = \Phi(\varepsilon \| ATTRACTOR\_VCG(i) - ATTRACTOR\_VCG(j) \|)$, where ATTRACTOR_VCG(i) stands for the point in phase space at time I, and ‖.‖ is the Euclidean norm used to calculate distance between points in phase space. ε is a cutoff distance, and Φ is the Heaviside function. The TRP will be a black and white plot with time on both the axes. The black dot indicates that the distance between the states ATTRACTOR_VCG(i) and ATTRACTOR_VCG(j) is below the cutoff distance ε The state ATTRACTOR_VCG(i) refers to ATTRACTOR_VCG(i) = [X(i), Y(i), Z(i)], which is a vector composed of 3-lead VCG at the time index i. As well as, the state vector ATTRACTOR_VCG(j) is at a different time index j[5, 18].

In RP, the diagonal lines represent the periodicity of patterns and the vertical lines show the nonlinear behaviors. The several measures derived from recurrence plot are listed below to use [19]:

Recurrence rate RR: the percentage of dark points in RP.

$$RR = \frac{1}{N^2}\sum_{i,j=1}^{N} R_{i,j}$$

Determinism DET: Percentage of recurrence points which form diagonal lines.

$$DET = \frac{\sum_{l=l_{min}}^{N} lp(l)}{\sum_{i,j}^{N} R_{i,j}}$$

Where P(l) is the histogram of the lengths l of the diagonal lines.

Longest diagonal line Lmax: The length of the longest diagonal line.

$$Lmax = \max(\{li;\ i=1\ldots Nt\})$$

Laminarity LAM: The percentage of recurrence points which form vertical lines.

$$LAM = \frac{\sum_{v=v_{min}}^{N} vp(v)}{\sum_{v=1}^{N} vp(v)}$$

Where P(v) is the histogram of the lengths v of the vertical lines.

Entropy ENTR: The Shannon entropy of the probability distribution of the diagonal line lengths p(l).

$$ENTR = -\sum_{l=l_{min}}^{N} p(l)\ln p(l)$$

Trapping time TT: The average length of the vertical lines.

$$TT = \frac{\sum_{v=v_{min}}^{N} vp(v)}{\sum_{v=v_{min}}^{N} p(v)}$$

Six recurrence statistics, namely RR, DET, LMAX, LAM, ENT and TT are exacted to quantify the nonlinear dynamic behaviors in each of the wavelet subseries.

3.4. Classification and Regression Tree

Decision tree is an example of machine learning technique. Decision structure is creates tree, as root node that has no incoming edges. All other nodes have exactly one incoming edge. In a Decision Tree,

each node applies the split criteria for the best selective attribute to make recursively best split with minimum impurity [22].
The split criterions are Gini index, the twoing rule, and maximum deviance reduction (also known as cross entropy).

The Gini's Diversity Index (gdi): is measure of node impurity, and works well for noisy data

$$\text{gdi} = 1 - \sum_{i=1}^{n} p^2(\text{i})$$

Where the sum is over the classes i at the node, n is the number of classes, and p(i) is the splitting samples of classes with class i that respond to the node. A node with just one class (a pure node) has Gini index 0; otherwise the Gini index is positive.

The twoing rule: is measure for deciding how to split a node.

$$\text{p(L)P(R)}\left(\sum_{\text{i=1}}^{\text{n}} |\text{ L(i)} - \text{R(i)}|\right)^2$$

Where L(i) is number of splitting samples from class i in the left node, R(i) is number of splitting samples from class i in the right node, and P(L) and P(R)are the number of splitting samples that split to the left and right.

Deviance (cross entropy): is the sum the probability distribution p(i)of overall the leaves.

$$-\sum_{\text{i}} \text{p(i)} \log \text{p(i)}$$

In my research, we apply Classification and Regression Tree of decision tree algorithms with gini index splitting criteria that give us the best result, as the following steps:

Firstly, all data are mixed classes that placed in root node. This node apply splitting rule (as gini index) and choose the best attribute to down split these samples to binary node. Then, the samples is respond of split criteria goes right node if its response yes. Otherwise it goes to left node. After that, the child node select another best attribute and apply split criteria and split its samples to left and right that depending on them response. Then repeat choose the best attribute can give the classifier best split and split the sample to left and right with minimum error [22, 23].

3.5. K-fold cross-validation, bootstrapping, and CART classifier

The k-fold cross validation and bootstrapping are recommended procedure for imbalance dataset which it applied on data set that contain majority acceptable class 769 and minority unacceptable class 92 and it works as follows[24, 25]:

1. Iteration i=1... K

2. Iteration j=1... N

2. a. Divide set A samples L, into K subsets of an equal number of observations. Let L1, L2... Lk is subsets.

2. b. Reconstruct the training set minority class by using random sampling with replacement to make its size similar as majority class.

2. c. Construct a CART classifier, g(X), from the k-1 subsets as training set.

2. d. Apply the classifier, g(X), to the excluded subsample, Lk, that contain1fold subset of K subsets.

2. e. Save the resulting classifier, g(X) as estimated target.

2. f. Repeat steps 3b, 3c, 3d and 3e to N iteration.

2. g. Assign the final estimated target for voting of N iteration by counting the number of votes is N/2. In other word, if number of voting to majority class is N/2 or more, it belongs to accepted class otherwise it belongs to minority class.

3. Shift the validation set to subset (i) of folds and takes the rest to training set.

4. Repeat steps 2, 3 to K of folds.

It's noted that, set A contains acceptable class and unacceptable class as shown in figure 4, we noticed the imbalanced sizes.

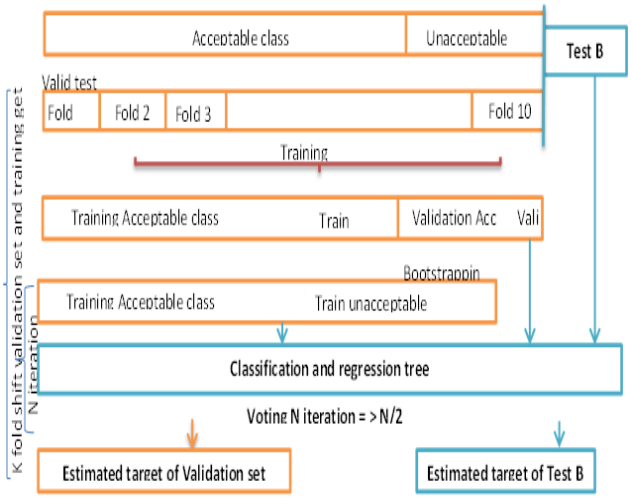

Figure 4: k-fold- cross validation with bootstrapping and

4. Discussion and Result

4.1. Dataset

In this study the ECG dataset were drawn from

PhysioNet challenge 2011 [3], it's including 1500 samples with 12-lead ECG. The samples are classified into training set (Set A) with 1000 samples and Test set (set B) with 500 samples. Each ECG sample is measured under the following characteristics: 12 leads are sampled at 500, 10 second duration, and with amplitude resolution 200m/v, 16-bit/sample.
Furthermore, the set A, training set (with known labels) is partitioned into two categories: 755 samples as acceptable class, and 255 as unacceptable class, and Set B (with unknown labels) are used for testing.

4.2. Design of experiments

In this paper, we discussed an algorithm designed to enhance the quality of ECG samples. This algorithm is mainly planned in three phases: The first phase is to eliminate some of noises specially high frequencies by applying band pass filter , other artifact as baseline wander, and loss skin contact electrodes by performing first order derivative. This procedure is discarded number of samples that maybe have one or more straight lines. In addition the straight line is founded dataset size 6 from acceptable class which is recognize as misclassified ,and 133 from unacceptable class in set A ,and 72 from test set(set B).

The remained of the dataset are ready to be with the next procedure. In second phase, firstly we derived the 3-lead VCG from 12-lead ECG. Then the wavelet packet is decomposed to into multiple wavelet scale. Finally we gather the signal component in the same scale to extract the recurrence feature. Consequently, the last phase is discussed the appropriate classifier algorithm (classification and regression tree) which is classified the recurrence features to the good quality or not. As shown in figure 4.

4.3. Numerical results

In this section, we have demonstrated various wavelets namely Coiflets, Daubichies, and Symlets with others important parameter such as various order of Butterworth filter, and various splitting criteria of CART classifier.

4.3.1 Experiment 1: Butterworth filter vs. wavelet family

The experimental results of comparison between wavelet families and the order filter of Butterworth are tested set A and test B as shown below in figure 5, 6.

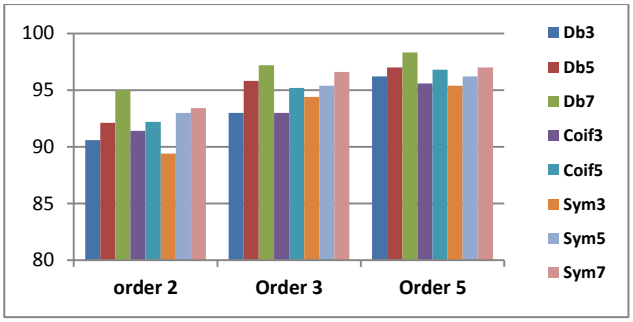

Figure 5: the comparison results between wavelet families and filter orders are tested on set A.

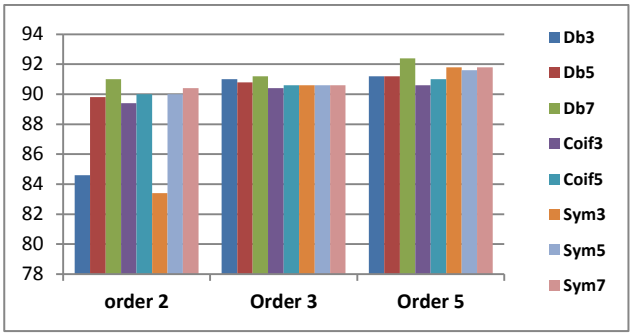

Figure 6: the comparison results between wavelet families and filter orders are tested on set B.

When gini index is the splitting criteria, The Daubechies7 (Db7) with 5th order filter gives the best result as compared to other combination of wavelet family and order filter.

4.3.2 Experiment 2: Butterworth vs. splitting Criteria

In this experiment, the other comparison results are shown in table 1, 2. When we select the Daubechies wavelet (Db7) parameter, the gini index of splitting criteria with 5th order filter of Butterworth gives the best result as compared to other combination of splitting criteria and Butterworth filter order.

splitting criteri / filter order	gdi	Twoing	Deviance
Order 2	95.00	94.40	94.00
Order 3	97.20	95.60	95.80
Order 5	98.32	96.80	97.20
Order 7	94.80	94.00	94.60
Order 10	87.60	85.80	85.00

Table 1: the comparison results between splitting criteria and Butterworth filter order for testing set A.

splitting criter / filter order	gdi	Twoing	Deviance
Order 2	91.00	90.80	91.00
Order 3	91.20	91.00	90.80
Order 5	92.4	90.80	91.20
Order 7	90.80	90.40	90.60
Order 10	84.60	84.80	82.60

Table 2: the comparison results between splitting criteria and Butterworth filter order for testing set B.

5. Conclusion

We have presented ECG healthcare monitoring through body sensor networks. The main approaches, such as ECG signal preprocessing, feature extraction using multi scale recurrence analysis, and the decision tree classifier, are previously discussed to improve the quality of ECG signals. The best result, when we test set A is 98.32 % for several variations of Butterworth filter order, types of wavelet, and several type of splitting criteria. Also, the best result when we test set B is 92.4, where the selected db7 from wavelet types, 5th fitter order of Butterworth, and gini index of CART is performed.

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