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ECG QUALITY EVALUATION BASED ON WAVELET MULTI-SCALE ENTROPY

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ABSTRACT

Electrocardiographic (ECG) analysis, which can be used to investigate the Cardiovascular physiological and pathological phenomena, has always been promoting new drug development and improving clinical diagnosis. With the modernization of medical treatment, evaluating the quality of ECG recordings and identifying whether they are diagnostically useful by information processing technologies become the focus of new researches. This paper presents a novel approach to appraise initial ECG recordings utilizing discrete wavelet transform (DWT) and multi-scale shannon entropy. A band-pass filter with 0.67Hz~40Hz bandwidth is proposed to preprocess the original ECG recordings and then the filtered ECG recordings are decomposed into different scales by DWT, and then after an iterative procedure based on comparing the entropy of each scale coefficient with trial threshold, the quality of ECG signals is assessed and divided into 'good quality and acceptable' (TypeI), and 'poor quality and unacceptable' (TypeII). The experimental results verify that the proposed method can effectively identify the TypeII of ECG recordings.

Keywords: *ECG, DWT, Wavelet, Entropy*

1. INTRODUCTION

According to the World Health Organization, cardiovascular diseases (CVD) are the first cause of death worldwide nowadays [1]. For the purpose of better dealing with the contingency and emergency of CVD, electrocardiographic (ECG) monitoring systems with their ability to provide tremendous diagnostic information have got a rapid development due to Holter ambulatory monitoring technology, computer networks technology and communication technology [2]. Common portable equipments such as mobile phones, watches, sensors of remote ECG monitoring systems and many other devices have been progressively implemented in this field and regarded as new platform for ECG signal acquisition and analysis [3]. As a result, even in the world’s impoverished and remote areas, it is possible to use one of these devices to collect ECG and assist CVD diagnosis.

However, ECG acquisition is subject to various factors including external electromagnetic interference, inappropriate placement of electrodes, respiration or motion from patients and poor skin-electrode contact and these factors exist rather remarkably on the occasion of portable apparatus for ECG monitoring. Noise generated in these cases may disturb the QRS complexes [4]. Regular noise[7] in these original ECG fragments is eliminated by traditional filter, but the QRS complexes have been damaged so severely that they still can not be recognized. Then these kinds of ECG fragments are regarded as 'poor quality and unacceptable' (TypeII). Otherwise we define the fragments as 'good quality and acceptable' (TypeI).

If the QRS complexes still could not be identified successfully after filtering, it is hard to decide whether the poor ECG recording indicates any meaningful physiological and pathological information, or just results from strong noise (another ECG recording should be acquired) [5]. In ECG analysis, the QRS complexes are the main clinical indicator for the determination of CVD [6] such as ventricular hypertrophy and ventricular flutter, etc. So TypeII should be screened out for other analysis if necessary, or else the subsequent blind processing for ECG of TypeII would be meaningless or at least it is diagnostically useless. Thus, pre-screening of the acquired ECG, or in other words, estimating the quality of raw ECG recordings and determining whether the ECG is of adequate quality for subsequent processing will be of great significance, especially in portable remote ECG monitoring systems.

During the years, several research papers have been putting emphasis on the development of methods for removing the majority sources of ECG corruption [7] as well as for ECG quality control [8]. Irena Jekova et al [9] present an algorithm to

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score the noise corruption level by analysis of ECG amplitudes and slopes in different frequency bands. All the five independent and separate noise tests exhibit satisfactory accuracy for the challenge database. The procedure manifests the noise levels corrupting the ECG components in different frequency bands could be considered as responsible measures of ECG quality. The algorithm used in the paper prefer the measure of information entropy variability rather than the energy brought by noise due to the fact that noise could lead to more significant increase in entopy, which is essiencal to distinguish physiological signals.

In this paper, we originally devised a wavelet-entropy-based ECG signal quality evaluation algorithm with the regard of entropy. Wavelet is capable of focusing on any frequency scale of the signal [10], therefore it can take into account noise information spreading across different frequency bands at the same time. Meanwhile, wavelet is well suited for the analysis of transient, time-varying signals, like ECG signals. According to the analysis above, through traditional filtering, TypeII has more redundant energy and information for the QRS identification in 5Hz~40Hz than TypeI. Consequently, to identify and locate TypeII in an ECG recording, we propose a wavelet decomposition to study noise distribution characters, and further obtain a verdict of noise by using information entropy mutation.

2. METHODOLOGY

2.1 Wavelet Multi-Scale Entropy

In information theory, entropy is a measure of uncertainty and average unpredictability in a random variable. Entropy has been continuously extended continuously and broadly applied in different scientific fields especially after the appearance of wavelet analysis. The combination of wavelet multi-scale analysis and information entropy unearths more potential information of signals. The procedure to calculate the wavelet multi-scale entropy of signal is as follows:

Firstly, the signal $S = f(t)$ should be decomposed into m scales by using discrete wavelet transform. Usually, the discrete wavelet function can be obtained by discretizing the scale parameter and the space parameter [11], and is commonly described as below:

$$\phi_{j,k}(t) = 2^{\frac{-j}{2}}\phi(2^{-j}t - k) \tag{1}$$

where j is scale factor and k is space factor. Then, the coefficients of discrete wavelet functions can be obtained:

$$C_{jk} = \int_{-\infty}^{\infty} f(t)\phi^{*}{}_{j,k}(t)dt = \langle f, \phi_{j,k} \rangle \tag{2}$$

In which * means conjugate operation. Thus the reconstruction formula can be written as

$$f(t) = C\sum_{-\infty}^{\infty}\sum_{-\infty}^{\infty} C_{jk}\phi_{j,k}(t) \tag{3}$$

where C is a constant dependent of the wavelet. Further the wavelet coefficient vector of scale j can be obtained as

$$W_j = (C_{j1}, \ C_{j2}, ..., C_{jn}) \tag{4}$$

where n is the length of the wavelet coefficient vector of this expression. If we consider each component of W_j as one value of a variable, then the weight probability of every component is

$$p_{ji} = C_{ji} / \sum_{i=1}^{n} C_{ji} \tag{5}$$

Thereupon wavelet multi-scale entropy of the j th scale can be calculated as follows [12]

$$H(W_j) = -\sum_{i=1}^{n} p_{ji} \log p_{ji} \tag{6}$$

The greater the value of $H(W_j)$ is, the larger uncertainty of information source will be[11, 13]. That is to say signal may contain more noise on j th scale.

2.2 The Proposed Method

When a signal is disturbed by noise, it has a greater value of entropy [13]. So we calculate the wavelet multi-scale entropy of an ECG recording on different scales and compare it with a given threshold. If the entropy is greater than the given threshold in some specific scales, we can define it as TypeII. Thus the proposed algorithm is described in detail as below:

- Acquire the target ECG recording $X(t)$.
- To remove the traditional noise in the original ECG recording, a band-pass filter of 0.67Hz~40Hz is implemented to $X(t)$ [14], after which the filtered ECG signal $X'(t)$ is achieved. Meanwhile, we detected the QRS complexes.

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- Create a sliding window with fixed length L and then slides along $X'(t)$ in proper sequence. For each sliding, intercept a total number of L points of signal $X'(t)$, the L-length signal is named as signal X_L .
- For each sliding, make the δ scales wavelet decomposition for X_L and acquire wavelet coefficient vector W_j of each scale.
- Calculate the wavelet multi-scale entropy $H(W_j)$ of several chosen scales covering primary energy distribution of signal and compare them with the given threshold of corresponding scale. If the amplitude of the entropy is over the threshold, define a variable Q_j of j th scale and assign its value as 1, otherwise 0.
- Make all Q_j process the logic and operation, if the result is 1 then TypeII is confirmed in this part, which indicates that at the same location of X_L in the original ECG recording, the signal is 'poor quality and unacceptable'.

The list of these steps can be explicitly displayed as the flow chart below in figure 1.

Actually, for the assumption that the strong interference in acquired ECG signal disperses in the frequency band of 5Hz-40Hz, only if a ECG recording is judged noised on all the selected scales could we define it as TypeII.

In the whole process, the value of δ is mainly determined by the property of our target ECG recordings. The window length L is calculated based on sampling rate, and a recommended valued can be experimentally 1~1.5 times of the sampling rate. Besides, the selection of the wavelet entropy threshold depends on trial, and the reference standards are mainly related to the specific ECG signal.

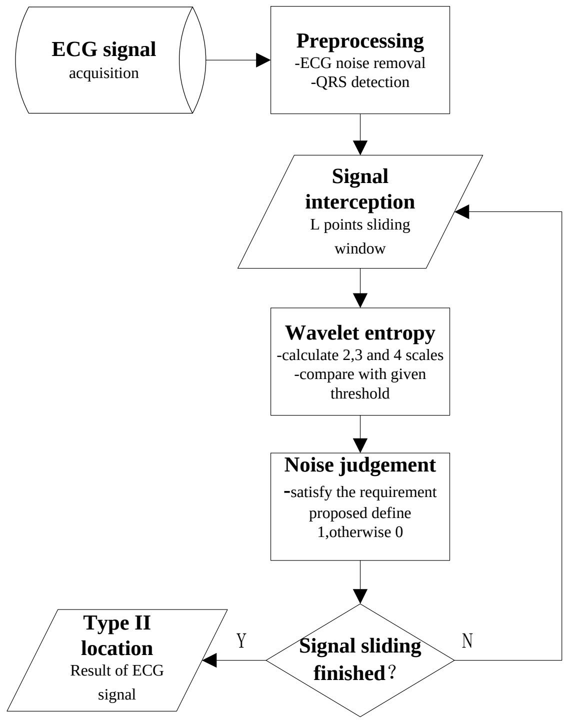

Figure 1: Wavelet Multi-Scale Entropy Based Algorithm Flow Chart

3. EXPERIMENTS AND RESULTS

The whole 25 experimental ECG recordings are afforded by Mindray Medical International Ltd and all recordings are digitized at 250 samples per second on each channel. We analyze the first one minute ECG recording from each sample and recognize the TypeII through the proposed method.

Moreover, we choose symlets wavelet (sym6) and define δ as 6 and then calculate the wavelet entropy of 2-4 scales owing to the assumption that the noise distributes in frequency domain across 5Hz-40Hz. In addition, the window length L is assigned 250 sample points.

The following table and figures show our experimental results and the assessment conclusion. Table 1 reveals TypeII location results of all the 25 recordings, which ideally fit our observation. In figures, we just list the results of recording 01, 03 ,11 and 13 in figure 2-5 to give typical examples (the red line represents the location results of QRS complexes).

Table 1: Typeii Location Results In First One Minite

Samples	Location results(unit:s)
recording 01	None
recording 02	None
recording 03	0-1,6-8
recording 04	None
recording 05	None

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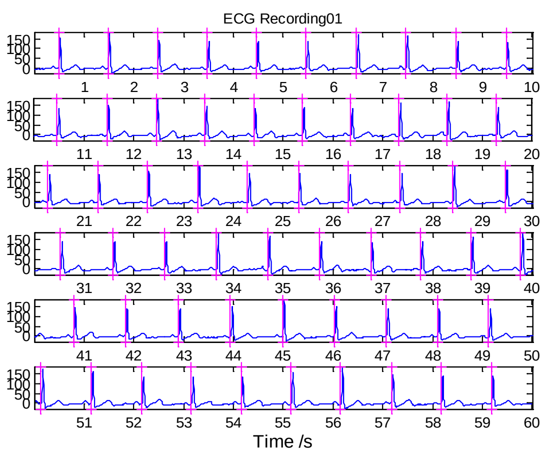
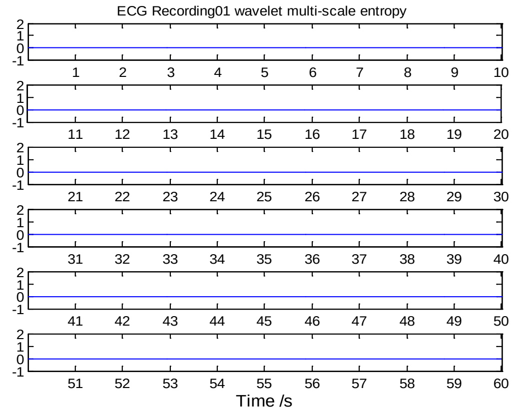
recording 06	None
recording 07	None
recording 08	52-55
recording 09	None
recording 10	42.5-43.5
recording 11	All
recording 12	None
recording 13	51.5-52.5
recording 14	None
recording 15	None
recording 16	None
recording 17	None
recording 18	None
recording 19	None
recording 20	None
recording 21	None
recording 22	None
recording 23	52-53, 54-55, 57-58
recording 24	None
recording 25	None

In the following figures, QRS complex positions in the original signal are revealed in part (a) of each figure and part (b) manifests the TypeII location map where value 1 represents TypeII. Figure 2 (a) indicates that recording 01 is good enough to detect QRS complexes accurately and agrees with Figure 2 (b) that no TypeII exists throughout the signal. On the contrary, circumstance of recording 11 is so severely corrupted by noise that the QRS complexes can hardly be effectively recognized, let alone to be analyzed for physiological and pathological information, and to our expectation, figure 4 (b) shows that TypeII exists almost everywhere in recording 11. Meanwhile, as for recording 03 and recording 13, Type II partially lies in ECG.

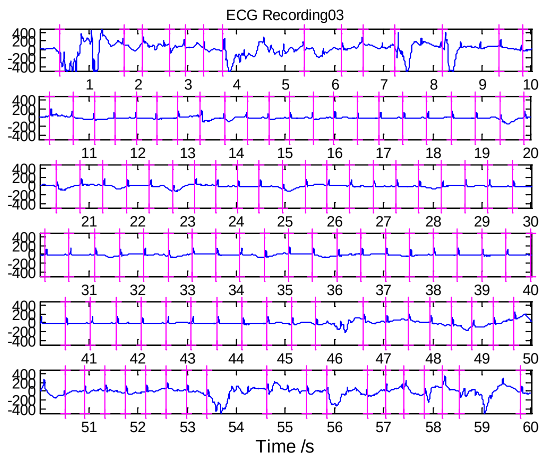


(a)

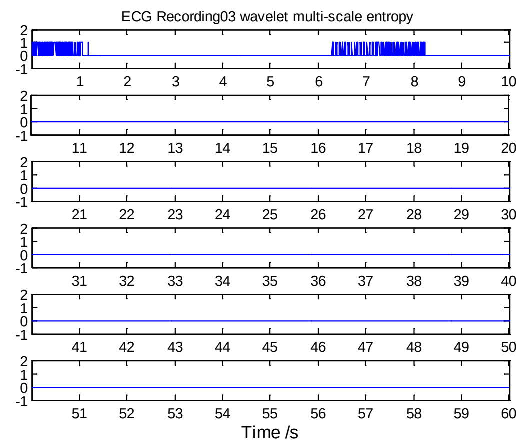


(b)

Figure 2: Experimental Results Of ECG Recording01 (A) Original ECG Recording01, (B) Typeii Positioning Results Of ECG Recording01 Based On The Proposed Algorithm



(a)



(b)

Figure 3:Experimental Results Of ECG Recording03 (A) Original ECG Recording 03, (B) Typeii Positioning Results Of ECG Recording03 Based On The Proposed Algorithm

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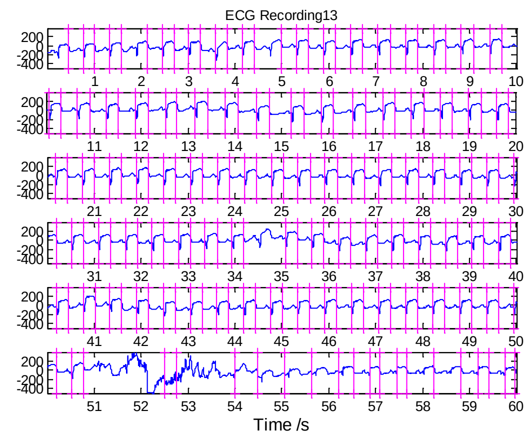
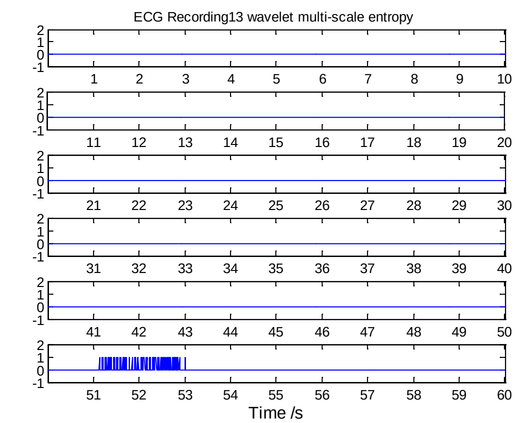
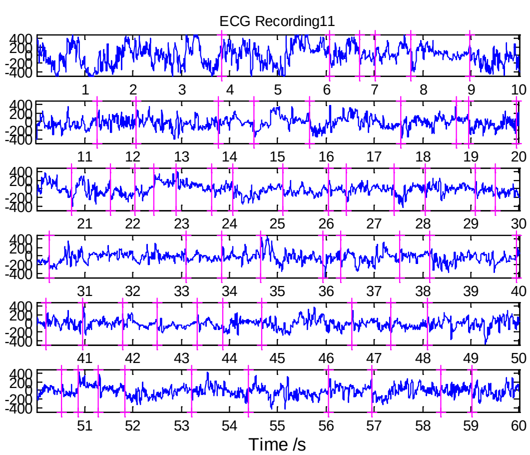


(a)

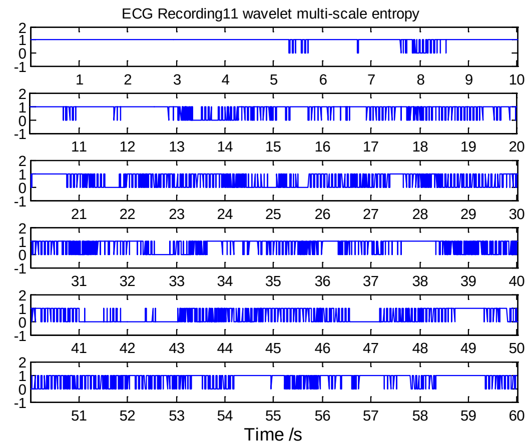


(b)

Figure 4:Experimental Results Of ECG Recording 13 (A) Original ECG Recording 13, (B) Typeii Positioning Results Of ECG Recording13 Based On The Proposed Algorithm



(a)



(b)

Figure 5:Experimental Results Of ECG Recording11 (A) Original ECG Recording 11, (B) Typeii Positioning Results Of ECG Recording11 Based On The Proposed Algorithm

4. CONCLUSION AND FUTURE WORK

In this paper, an algorithm based on wavelet multi-scale entropy is presented in quality control of ECG recordings. The selection of algorithm parameters is easy and intelligible to carry out according to our requirements. Moreover the results infer that the corruption of noise leads to information augment of different frequency bands. Hence the proposed technique has proven accurate especially in the presence of different kinds of noise. To sum up, wavelet multi-scale entropy is competent to reflect the noise corruption level in signal dynamics. Compared with other previous methods, we skip those easily detectable situations like constant sections of a signal result from aborted electrode attachment while pay more attention to intricate and strong noise in signal. And we evade detecting all implemented noise such as power line interference and baseline wander dependently, thereby improving the efficiency of the evaluation and preserving the characteristics of the overall signal.

The ECG prescreening insures the precision and efficiency of the subsequent data processing. In terms of popularizating telemedicine and enhancing its credibility, this proposed algorithm is to assess the quality of the acquired ECG recording, and thus equipping electrocardiogram monitor with prescreening function.

A great deal of further work would be useful. Our algorithm just performs well for Mindray dataset. We need to test its validity in practical use. Besides, further criterion should be put forward to abandon ECG recordings according to their TypeII

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map. Posteriorly, a better and faster process to satisfy the increasing requirement of real-time prescreening is desired. Also some other Signal transform algorithms are needed to achieve a better result.

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