ECG Data Compression by Multiscale Peak Analysis

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Abstract

This paper presents an ECG data compression technique by the multiscale peak analysis. We define the multiscale peak analysis as the wavelet maxima representation of which the basic wavelet as the second derivative of a symmetric smoothing function. The wavelet transform of an ECG shows maxima at the start, peak and stop points of five transient waves P through T. The number of wavelet maxima is expected to be less than the number of original data samples. The wavelet maxima can be enough to reconstruct original signals precisely. The wavelet maxima representation can hence lead to the ECG data compression and analysis. The compressed data still keep the peaks of QRS waves, abnormal behavior search will be feasible in practice. The result of the compression shows that a normal ECG data is compressed by a factor 10.

1. Introduction

Electrocardiogram (ECG) is generated by the ambulatory measurement. Recorded samples are more than 10 millions a day. The amount of ECG data is so large that two problems can arise: data analysis and data compression.

Computerized analysis algorithms[1] have been proposed to detect abnormal behavior in the ECG data. Especially, analyzing QRS complexes is important for the diagnosis. QRS detection algorithms[1] which measure the peak locations in QRS complexes are hence developed.

The other problem is data compression to record long period data in a small-capacity storage. ECG data compression can be divided into two groups: direct methods and transform methods[2].

Direct methods are performed by irregular sampling of original waveforms in the time-domain. Transform methods are based on orthogonal transforms (Fourier, Walsh, K-L, DCT or wavelets [6]) and achieve higher compression ratio than direct methods. It is not yet possible to detect QRS waves from compressed data by orthogonal transform methods. If compressed data still keep the peaks of QRS waves, abnormal behavior search will be more feasible in practice. Also, it needs neither reconstrction nor additional QRS detection processing.

In this paper, we introduce an ECG data compression algorithm which has following advantages:

(1) Compression ratio is higher than direct methods.
(2) QRS complexes can be detected in compressed data.

The proposed ECG compression technique is based on the wavelet maxima representation[3-5]. The wavelet maxima representation was introduced for multiscale edge analysis[3]. In image analysis, the basic wavelet is defined as the first derivative of a smoothing function[3]. The wavelet maxima represent the location of edges. In ECG analysis, we define a basic wavelet as the second derivative of a symmetric smoothing function. With this wavelet, a wavelet maxima represent the location of a peak of the waveform. The wavelet transform of an ECG shows maxima at the start, peak and stop points of five transient waves P through T. The number of wavelet maxima is expected to be less than the number of original data samples. The wavelet maxima representation can hence lead to the ECG data compression and analysis. In section 2, we explain wavelet transforms and the wavelet maxima representation. Section 3 describe the ECG data compression by the wavelet maxima representation. Compression ratio and reconstruction precision are also given.

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2. Wavelet Maxima Representation

The discrete dyadic wavelet transform is defined as a inner product between wavelets $g_i(x)$ and a signal $f(x)$[3-6].

$$W_i(n) = \langle g_i(x - n), f(x) \rangle \qquad (1)$$

where $< \cdot >$ denotes the inner product. $g_i(x)$ are produced from the basic wavelet g(x) by scaling with factor 2^{-i}. A signal $f(x)$ is represented by $W_i(n)$ (i=1 through M) and a smoothed signal

$$S_M(n) = \langle 2^{-M} h(2^{-M}x - n), f(x) \rangle \qquad (2)$$

where h(x) is the smoothing function. The wavelet maxima is defined at a point n where the wavelet transform satisfies

$$W_i(n+1) \leq W_i(n) \qquad (3a)$$

and

$$W_i(n-1) \leq W_i(n) \qquad (3b)$$

for $W_i(n) > 0$,

$$W_i(n+1) \geq W_i(n) \qquad (4a)$$

and

$$W_i(n-1) \geq W_i(n) \qquad (4b)$$

for $W_i(n) < 0$. The wavelet maxima point n in the ith scale is denoted by $m_{i,k}$. The wavelet maxima representation describes the original signal by wavelets maxima $W_i(n)$ at $n = m_{i,k}$ and a discrete smoothed signal $s_M(n)$.

In detection of QRS complexes, a peak detector is a filter of which impulse response is the second derivative of a symmetric smoothing function[1]. The peak detection is done by seeking maxima points of the filter output. We extend the single peak detector to a set of peak detectors which is defined at several resolution. If the impulse response is an admissible wavelet, and if the multiscale peak detectors are derived by scaling, then we obtain a characterization of a wavelet maxima representation. Hence the multiscale peak analysis describes the evolution of peaks across different scales and entire sets of those multiscale peaks can reproduce the original waveforms.

Fig. 1 shows the multiscale peak analysis of an ECG waveform. Generally one-period segment in ECG waveforms consists of a transient part and a slowly-varying part. The transient is an abrupt large amplitude changes called Q, R and S. The long-period trends are slow and called P and T. Thus the multiscale peak analysis of P and T waves produces a few peaks only in larger scales. In contrast, a fast change component such an Q, R and S leads to a sequence of several peaks across coase-to-fine scales. If the orthogonal wavelet transform is applied to peak point detection, the sampling grid of the orthogonal wavelets is too coarse to detect peak point.

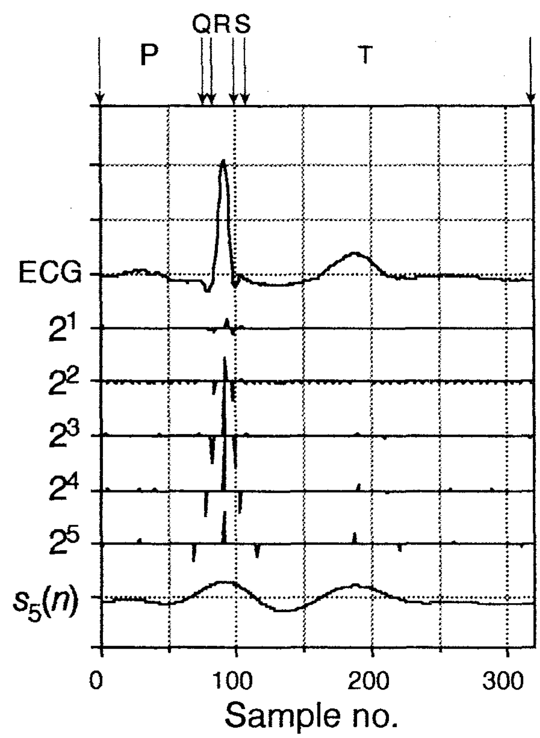

Fig. 1 Multiscale peak analysis of an ECG waveform

The reconstruction from the wavelet maxima representation is executed by iterative projection between two closed convex spaces[3, 7]. One of these spaces is the linear space of all the possible wavelet transforms. The other is characterized by the

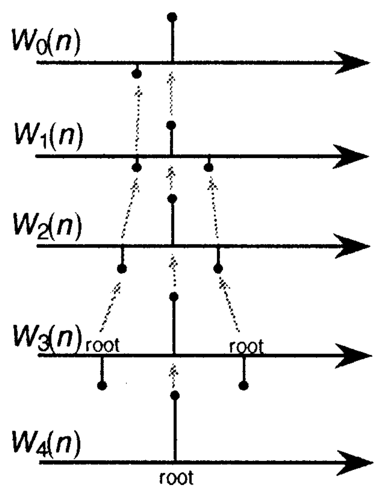

Fig. 2 Seeking root maxima and other maxima

maxima representation. The iteration of projections guarantees the convergence to the intersection of two spaces. Every function in the intersection approximates the wavelet transform of the original signal. We can hence get an approximation of the original signal by the inverse wavelet transform of the result of iteration.

3. ECG Data Compression

We then apply the wavelet maxima representation to an ECG data taken from MIT-BIH Arrhthmia ECG Record 103. The ECG is recorded by the Holter ECG recorder during about 30 minutes at sampling rate 360Hz with wordlength 11 bits.

Every maximum is quantized to 8 bits. Maxima that shrinks to zero after quantization are removed. We record the wavelet maxima by following process.

(1) Seek a maximum of the wavelet transform at the largest scale. If the maximum was found, it is defined as a *root* maximum and record its position and value. If the *root* maximum was not found, seek the *root* at next finer scale.

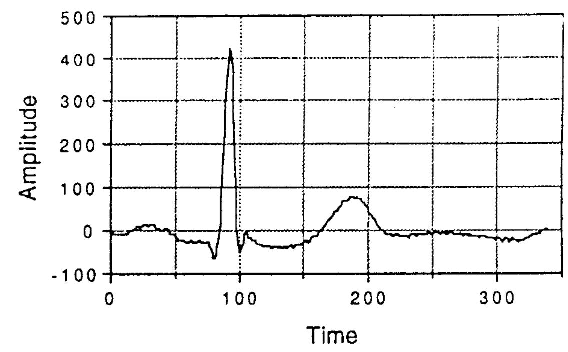

Fig. 3 Original waveform

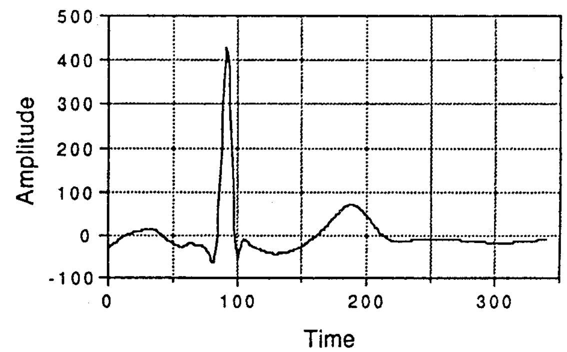

Fig. 4 Reconstruction after compression

(2) At next finer scale, seek maxima of which sign is same as the root maximum. Next, select a maximum which is the closest to the root maximum. If the closest maximum is found, record its value and the distance between its position and the position of the root maximum. Next, repeat seeking of a maximumu at next finer scale. If a maximum is not found, record a seek-stop code and repeat from (1).

Fig .2 shows the seeking process. Every maxima locates around peaks of the original signal. We hence record the position difference for efficient entropy coding, The Lempel-Ziv coding is applied for position, distance and amplitude data respectively. The smoothed signal $s_M(n)$ is recorded in the form of the position and the value of extrema. $s_M(n)$ is also recovered through the convex projection. The original waveform and the reconstructed waveform are shown in

Fig. 3 and Fig. 4. The rejection of small maxima by quantization reduces the noise and preserves sharp variations of Q, R and S waves. In this case, the amount of data decreased to 1/10.

Fig 5. plots the compression ratio versus reconstruction error in terms of percent root-mean-square difference (PRD). In this case, we quantized value of maxima to 8, 7 or 6 bits. The solid curve indicates the PRD vs by SAPA (Scan-Along Polygonal Approximation) [2]. The SAPA is the piecewise linear approximation and widely used for ECG data compression. In compression by SAPA, Lempel-Ziv coding is also applied. In all compression, PRD of the proposed method is 3 or 2% superior to SAPA.

5. Conclusion

In this paper, we proposed an ECG compression technique by the wavelet multi-scale peak analysis. ECG waveforms, especially the swift changes in Q, R and S waves are characterized in the multiscale peaks. The compression ratio is higher than the direct method (SAPA). Since the compressed data still keep the peaks of QRS waves, abnormal behavior search will be feasible. The wavelet multi-scale peak analysis will lead an unified approach to both ECG compression and analysis.

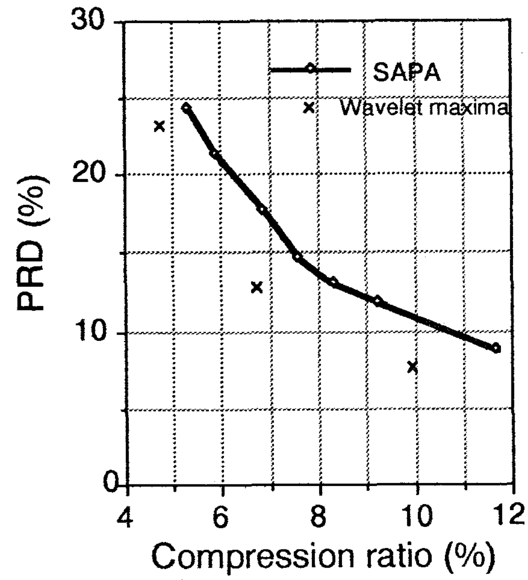

Fig. 5 Compression ratio vs reconstruction error

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