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DWT Based Detection of R-peaks and Data Compression of ECG Signals

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An algorithm based on discrete wavelet transforms (DWT) for detection of R-peaks, computation of R-R interval and data compression of ECG signals is presented. The proposed algorithm is robust to noise. Results are provided that demonstrate the performance of the algorithm.

Indexing terms: DWT, R-peak detection, ECG data compression.

DETECTION of R-peaks and computation of R-R interval of an ECG record is an important requirement of comprehensive arrhythmia analysis systems. A number of methods both hardware and software, have been developed for the detection of QRS complex [1-3].

Another area of active research in the analysis of ECG is data compression, which finds use in the storage and transmission of the signal. A number of methods based on discarding redundant samples in time and frequency domains have been proposed for compressing ECG [4].

R-peak detection is difficult, not only because of the physiological variability of the QRS complexes, but also because of the various types of noise that can be present in the ECG signal. Of the many QRS detectors proposed in the literature, few give serious enough attention to noise reduction.

Due to their efficiency for processing nonstationary signals and robustness to noise, wavelet transforms have emerged as powerful tools for processing ECG signals [5-7].

In this paper, a unified approach is presented for detection of R-peaks, computation of R-R wave interval and data reduction of ECG signals using the Daubechies discrete wavelet transform (DWT) algorithm. The robustness of the algorithm to noise is illustrated through simulation studies. Further, the percentage data compression of ECG signal and percent mean square difference (PRD) obtained with the algorithm for various wavelet filter lengths have been reported.

BASICS OF WAVELET TRANSFORMS

For convenience of the reader, this section briefs the basics of the wavelet transforms [8-10]. Given a time varying signal $x(t)$, wavelet transforms consist of computing coefficients that are inner products of the signal and a family of "Wavelets". In a continuous wavelet transform, the wavelet corresponding to scale a and time location b is

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\, \psi \left(\frac{t-b}{a} \right) \tag{1}$$

where

$\psi(t)$ is the wavelet "prototype" which can be thought of as a band pass function. $\psi(t-b)$ is the translated version of $\psi(t)$. This kind of translation is required for the wavelet to cover the whole of the time axis and it is achieved by varying the shift parameter b.

The factor $1/\sqrt{a}$ is included for energy normalization, that is to ensure that wavelets have the same energies at all scales for all values of a.

The continuous wavelet transform (CWT) is given by the following equation

$$\text{CWT}\,[x(t); a, b] = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\, \psi^* \left(\frac{t-b}{a} \right) dt \tag{2}$$

The '*' stands for complex conjugate.

The DWT has been recognised as a natural wavelet transform for discrete time signals by several investigators. Both time and time-scale parameters are discrete. As far as the structure of computations is concerned, the DWT is in fact the same as an octave-band filter bank. The filter bank has a regular structure, it is easily implemented by repeated application of identical cells. It is also computationally efficient. Therefore, if the computation of a wavelet transform can be reduced to a DWT, then the resulting implementation is likely to be efficient [10]. The parameters a and b are discretized as

$$a = a_0^j \text{ and } b = ka_0^j \tag{3}$$

where k is an integer.

These yield the wavelet series with coefficients which

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are nothing but appropriately sampled values of the continuous wavelet transform. Generally a_0 is chosen as 2 and this particular case is known as the dyadic wavelet transform (DyWT). Since the CWT is sampled on a dyadic grid, the wavelets used in this are of the form

$$\psi_{J,k}(t) = 2^{-j/2}\, \psi(2^{-j} t - k) \qquad (4)$$

The DyWT of a signal $x(t)$ is given by the following equation

$$\mathrm{DyWT}\,[b, 2^j] = \frac{1}{2^j} \int_{-\infty}^{\infty} x(t)\, \psi^*\left(\frac{t-b}{2^j}\right) dt \qquad (5)$$

The DWT of discrete singal $x(n)$ achieves a multi resolution decomposition on a finite number of scales denoted by $j = 1,2, \ldots J$ and the signal $x(n)$ is represented in terms of wavelet and scaling functions as

$$x(n) = \sum_{j=1}^{J} \sum_{k} d_{j,k}\, \psi_{j,k}(n) + \sum_{k} c_{j,k}\, \phi_{j,k}(n) \qquad (6)$$

The $\psi_{J,k}(n)$ are the synthesis wavelets, the discrete equivalents to $2^{-j/2}\, \psi\,(2^{-j} t - k)$. An additional (low pass) term is used to ensure perfect reconstruction; the corresponding basis functions $\phi_{J,k}(n)$ are called scaling functions.

The DWT computes "Wavelet Coefficients" $d_{j,k}$ for $j = 1, 2, \ldots J$ and scaling coefficients $c_{j,k}$ given by

$$c_{j,k} = \sum_{m} h(m-2k)\, c_{j+1},\, m$$

$$d_{j,k} = \sum_{m} g(m-2k)\, c_{j+1},\, m$$

The c's in a DWT are called the smooth coefficients and d's are known as the detail coefficients. h and g are the discrete filters representing the scaling and wavelet functions respectively.

The inverse DWT reconstructs the signal from its coefficients by using eqn (6). The DWT may be computed iteratively, the starting point of course the original signal which has a higher resolution than any of its approximation. Starting with the signal, one can obtain the detail coefficients corresponding to the approximation of the signal at various resolutions, until a trivial number of smooth coefficients remain, which correspond to the coarsest resolution used. If dyadic scales are used, the number of coefficients of the form $d_{j,k}$ at each successive scale is half the number of the previous scale. It the signal has N samples, the number of DWT coefficients generally computed are

$$\frac{N}{2} + \frac{N}{4} + \frac{N}{8} + \cdots + \frac{N}{2^j} + \frac{N}{2^j}$$

where j is the highest scale of coarsest resolution used.

Algorithm for detection of R-peaks, computation of R-R wave time interval and data reduction of ECG signals

It has been proved that if a wavelet function is chosen which is the first derivative of a smoothing functions, then the local maxima of the DyWT indicate the sharp variations [7] in the signal, whereas local minima indicate the slow variations. Such wavelets are used to detect the instant of R peak in the R peak detecter.

Generally, the DyWT is computed at scales $a = 2^j$ for all j ($j = 1, 2, 3, \ldots$). However, since ECG is a low frequency information (0.05 to 100Hz) it is observed that it is sufficient to compute DyWT only at few scales, in order to estimate the R-R wave interval very accurately with the advantage of reducing computational complexity.

Wavelet transform is a useful tool for data compression since most of the DWT coefficients are small compared to the sample values of the original signal. Thus the DWT expansion has a lower entropy than the original signal, which implies that fewer bits need to be transmitted for the small coefficients. Also, it can be seen that not much distortion is introduced, if some of the coefficients in the DWT expansion are entirely neglected (i.e., set to zero) and the original signal is reconstructed using the inverse DWT.

The DWT based algorithm for detection of R-peaks, computation of R-R wave interval and the data compression of ECG signal as follows.

Step 1: Set segment length = L ms and $j = 1$.

Step 2: Read L ms of the jth segement of the ECG signal.

Step 3: If end of file occur within L ms, then go to step 14.

Step 4: Set $i = i_l$ (lower resolution) and computes DyWT $(b, 2^i)$.

Step 5: If the maximum of DyWT$(b, 2^i)$ is less than the threshold, then go to step 12.

Step 6: Compute DyWT $(b, 2^{i+1})$.

Step 7: Locate local maxima of DyWT $(b, 2^i)$ and DyWT$(b, 2^{i+1})$ which exceed 0.5 times global maximum across two dyadic scales.

Step 8: If the locations of the local maxima of DyWT $(b, 2^i)$ and DyWT $(b, 2^{i+1})$ are the same, then go to step 11.

Step 9: Set $i = i + 1$.

Step 10: If i is less than i_u (upper resolution), then go to step 5. If i is greater than i_u, then go to step 12.

Step 11: Output the onset of the R-R wave interval = locations of thresholded local maxima of DyWT $(b, 2^i)$

output the R-R wave interval = the time interval between two successive local maxima and then go to step 13.

Step 12: Lack of QRS complex in the segment.

Step 13: Compute the DWT of the jth segment of the signal.

Step 14: Set DWT coefficients to zero whose value is less than the thresholded value.

Step 15: Set $j = j + 1$ and go to step 2.

Step 16: Stop

In the above algorithm, i_l and i_u stand for lower and upper values of i.

RESULTS

The original ECG signal sampled at 200 samples per second is shown in Fig 1*a*. The algorithm has been applied to the noisy ECG signal with SNR −1.7353 dB as shown in Fig 1*b*. The noise used here is Gaussian. The SNR is the ratio between the signal power to the noise power. The DyWT of the noisy ECG signals are obtained using Daubechies wavelet functions corresponding to various scales and for different filter lengths. The DyWT exhibits local maxima corresponding to the onset of R-R interval across all these scales. The locations of the threshold local maxima of DyWT of the noisy ECG signal are matched at scales $a = 2^3$ and $a = 2^4$ for all the filter lengths. These are shown in Figs 1*c* and 1*d* with the filter length = 6. The R-R wave interval is estimated from the DyWT obtained at scale $a = 2^4$. The estimated R-R wave time interval is found to be 0.505 seconds.

Here, the SNR −1.7353 dB is chosen to show the robustness of the algorithm to very high noise levels. DWT representation of the ECG signal involving a minimum number of significant coefficient (with threshold = 30dB) for data compression of the ECG signal has been obtained using the Daubechies wavelet varying the filter length from 2 to 20. All DWT coefficients which are at least 30 dB less than the maximum coefficient are discarded. The original and reconstructed signal for wavelet filter lengths 2 and 12 are shown in Fig 2*a* and 2*b* respectively. The percent root mean square difference (PRD) is calculated as follows.

$$\text{PRD} = \sqrt{\frac{\sum_{i=1}^{n} [x_{org}(i) - x_{rec}(i)]^2}{\sum_{i=1}^{n} x_{org}^2(i)}} \times 100 \quad (7)$$

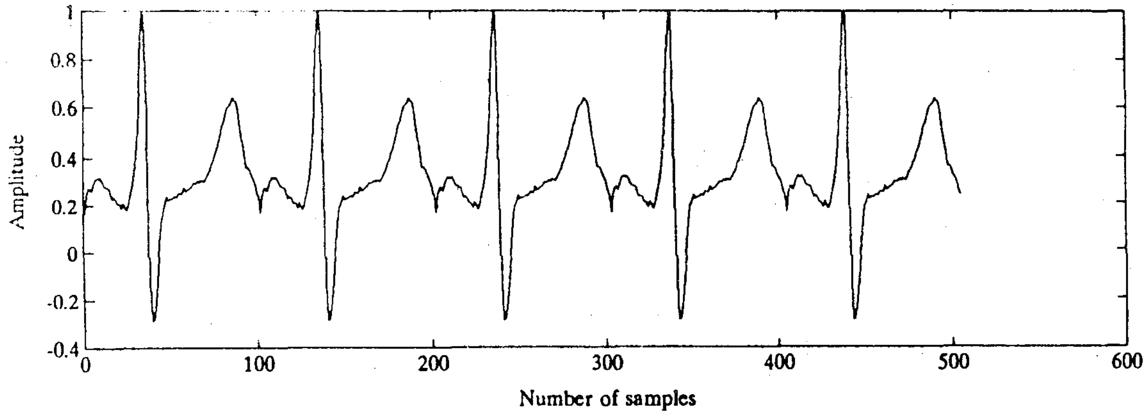

Fig 1*a* Original ECG signal

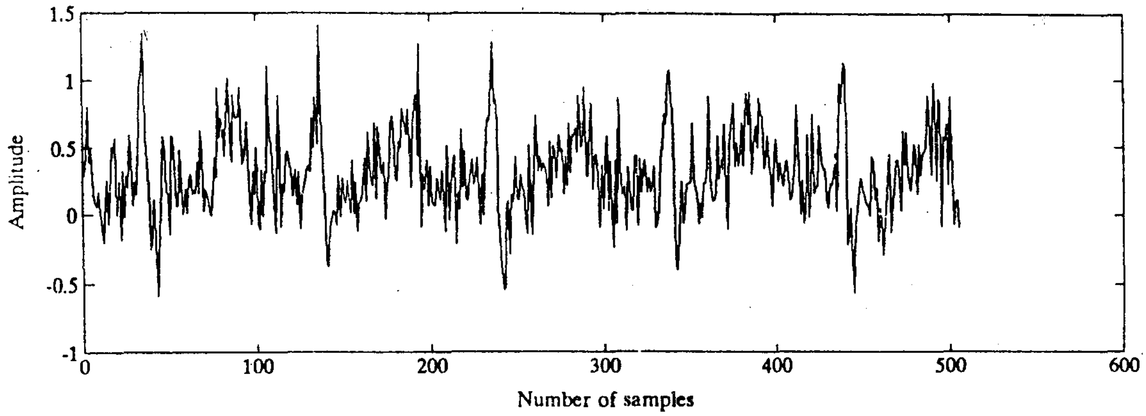

Fig 1*b* Noisy ECG signal with SNR = −1.7353 dB

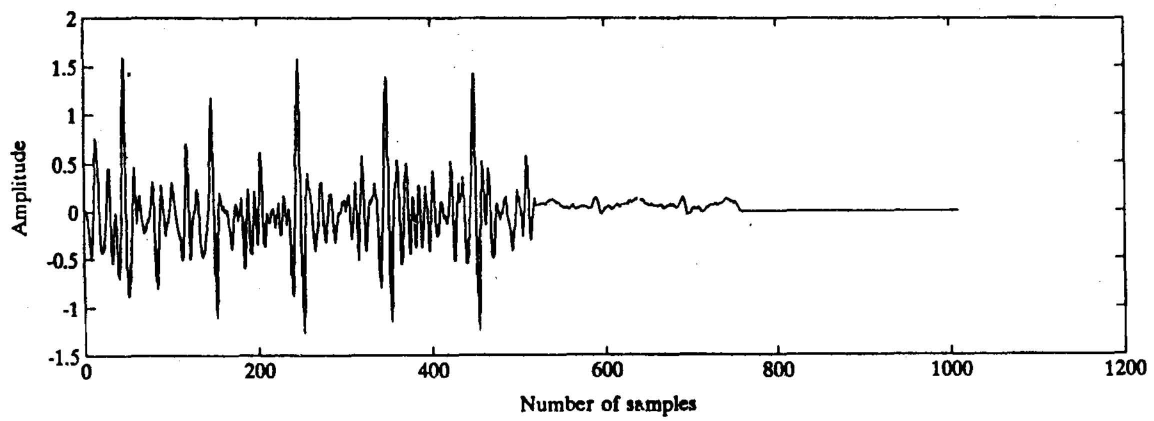

Fig 1c WT of noisy ECG signal at scale 2^3 with $N = 6$

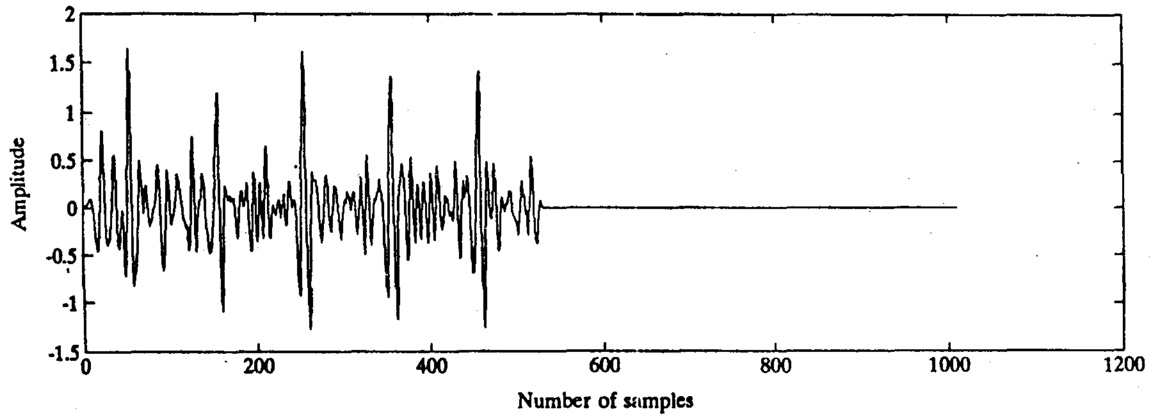

Fig 1d WT of noisy ECG signal at scale 2^4 with $N = 6$

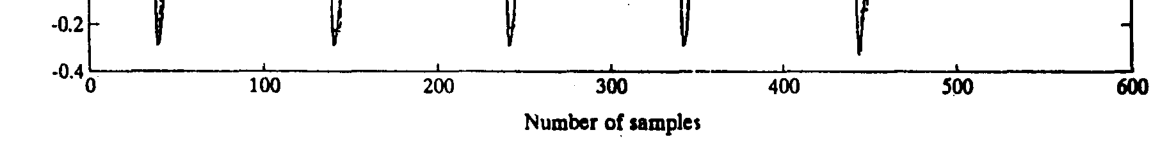

Fig 2a Original and reconstructed ECG singal with $N = 2$

where x_{org} and x_{rec} are samples of the original and reconstructed ECG signal.

The results of data reduction and PRD for various wavelet filter lenghts are tabulated in Table 1. As a trade-off between % data reduction and PRD, from Table 1 it is found that the wavelet filter length 12 is best suited for ECG data compression. It may be noted that the percentage data reduction and PRD obtained are superior to that were reported in [4] for the other data reduction algorithms. The most commonly used direct data compression method CORTES yields about 80% data reduction with PRD of seven [4]. The present DWT method yields about 82% data reduction with PRD of 5.

CONCLUSIONS

In this paper, algorithm based on discrete wavelet transforms for detection of R-peaks, computation of R-R wave time interval and data compression ECG signals has been presented. The advantage of the DWT based data reduction is that no assumptions need to be made

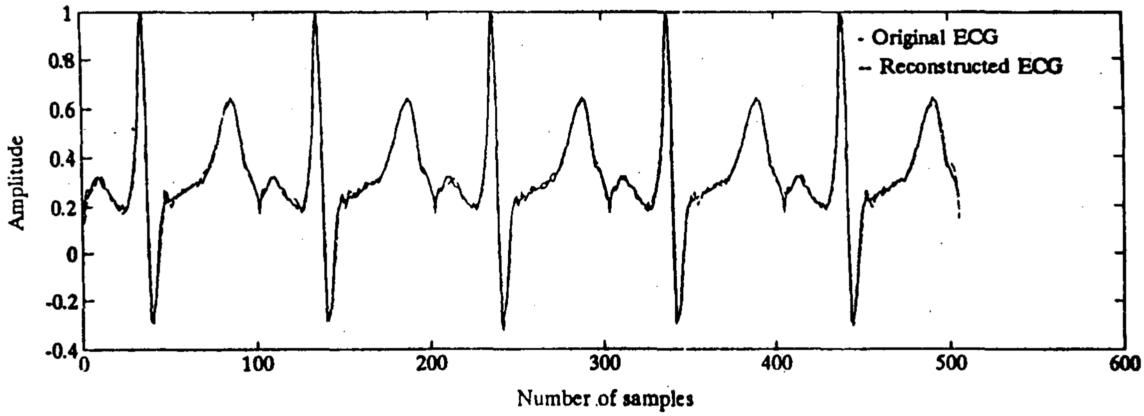

Fig 2*b* Original and reconstructed ECG singal with $N = 12$

TABLE 1 Comparison of ECG data compression and PRD for various wavelet filter lengths

Wavelet filter length	Threshold in dB = 30	
	% data reduction	PRD
2	88.3168	15.1135
4	85.5446	9.3278
6	82.7723	7.0535
8	82.7723	6.3031
10	80.0	4.9891
12	81.7822	5.0553
14	80.7921	5.0789
16	78.2178	4.5583
18	76.4356	3.9162
20	78.2178	4.4816

regarding the nature of the signal to be compressed and the percentage data reduction and PRD are superior to that were obtained with the other data reduction algorithms.

The advantages of the DWT based detection of R-peaks and computation of R-R wave time interval are that it does not assume stationarity or quasi stationarity within the analysis segment, detects R peaks and estimates R-R wave interval very accurately exhibiting robustness to noise and this algorithm is computationally simple since it needs to compute the DyWT at three or four scales.

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