Adaptive Discrete ECG Representation - Comparing Variable Depth Decimation and Continuous Non-Uniform Sampling

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Abstract

This paper compares two methods of non-uniform ECG sampling: the variable depth decimation (VDD) and the continuous non-uniform sampling (CNU).

The VDD algorithm uses the wavelet-based time-scale decomposition of the segmented ECG in which the high frequency scales representation is eliminated for the signal sections of narrower bandwidth (e.g. T-P segment). In result, the signal is locally decimated down to the level depending on the expected bandwidth. The CNU algorithm uses a soft estimation of the length for each subsequent sampling interval on a basis of expected local bandwidth of the signal.

For ECG records from the CSE Multilead Database the average efficiency of the VDD algorithm is significantly higher (4.26) than the efficiency computed for the CNU method (3.01). Unfortunately, the global reconstruction error (PRD) is also higher for the VDD (0.40%) than for the CNU algorithm (0.22%).

1. Introduction

Optimizing the transfer of the fundamental vital sign (electrocardiogram, ECG) is the focus point of high priority in the modern information society. The discrete ECG representation commonly uses the uniform sampling that is easy to manage but not optimal for this variable-bandwidth signal. The use of non-uniform sampling adapted to the local signal contents is an interesting alternative for its two advantages: reduced data volume and improved signal-to-noise ratio.

This paper describes the comparison of two methods of non-uniform ECG sampling developed currently in our laboratory: variable depth decimation (VDD) [1] and continuous non-uniform sampling (CNU) [2]. Both methods require as input an ECG-based function defining the instantaneous bandwidth of the signal. For the comparison purpose the same local bandwidth function related to the P-QRS-T waves' start- and endpoints was used in each case.

Main novelty of this approach is the use of medical information, extracted from the signal by the specialized algorithm as it were used for the diagnostic purpose, to influence the sampling parameters. Consequently, the adaptive discrete representation reflects the non-uniform temporal distribution of medical data in the ECG signal.

The VDD algorithm uses the wavelet-based time-scale decomposition of the segmented ECG in which the representation of scales corresponding to high frequency is eliminated for the signal sections of narrow bandwidth. In result, the signal is locally decimated down to the level depending on expected signal bandwidth.

The CNU algorithm uses a soft estimation of the length for each subsequent sampling interval on a basis of expected local bandwidth of the signal. First, the adaptive anti-alias filtering eliminates the components of frequency exceeding the local bandwidth of cardiac representation. Then, the positions of irregularly spaced samples are computed and their values are estimated with use of cubic splines interpolation.

2. Principles of adaptive representations

This section guides into details about the detection of local diagnostic information density and explains the principles of both compared optimisation algorithms.

2.1. The local bandwidth of the ECG

The segmentation of the ECG signal may be performed by any subroutine, complying with the diagnostic standards [3, 4]. For testing the optimisation algorithms we used a typical subroutine originally designed for an ECG recorder or the reference segmentation points provided by the CSE Multilead database [5]. The segmentation bases on the ECG signal sampled at a constant rate (500 Hz).

The temporal relationship of medical data vulnerability resulted from our previous experiment with controlled data cancelling in time-frequency domain [6] was used as an estimate of the required local bandwidth of the ECG signal. Other ECG-related functions may also play this role accordingly to the particular diagnostics interest.

The shape of this standard importance function is piecewise fitted with use of the cubic spline interpolation into the segmentation points detected individually for each heartbeat (fig. 1).

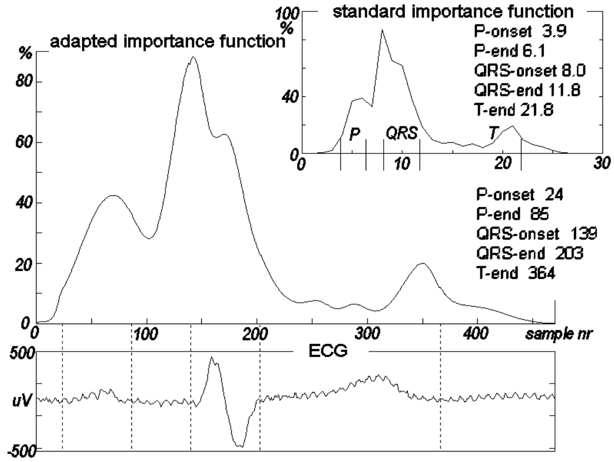

Figure 1. Standard importance function and its version adapted to the ECG signal (CSE, file Mo001)

2.2. The variable depth decimation

The decimation of a discrete signal representation is commonly implemented with use of filter banks. An interesting algorithm is the lifting wavelet transform (LWT), for its relatively high computational efficiency and because it maps integers to integers directly [7, 8].

The single stage of lifted wavelet signal decomposition (fig. 2) starts with splitting the signal into two half-length components, what is called the trivial wavelet transform or the Lazy Wavelet. Next, the half-band properties of these strings are improved using the lifting and the dual lifting alternately. The lifting operation means here increasing the number of vanishing moments of a wavelet without any changes of its properties.

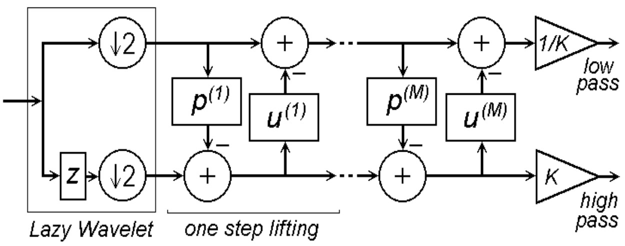

Figure 2. The computing scheme of one stage of wavelet decomposition using M lifting steps

A dual lifting step consists of applying a low-pass integer filter p to the even samples and subtracting the results from the corresponding odd samples. A primal lifting step, used immediately thereafter, consists of applying a high-pass integer filter u to the odd samples and subtracting the results from the corresponding even samples. The lifting algorithm generates two decimated data strings: the low-pass coarse signal and the detail high-pass signal. The lifting scheme is a reversible process in the integer-format environment thus the resulting stings contain complete original information.

Because nearly a half of the signal length is sampled at the minimum rate, the decimation is performed continuously and yields an uninterrupted coarse approximation of the ECG. Within the P, QRS and T waves, that start- and endpoints are valid also in the time-frequency domain, the signal is completed by the details representing high frequency bands. These components appear occasionally depending on the adapted importance function and thus need additional synchronization byte referring to the continuous signal (figs. 3, 4). Adding the high frequency information to the approximation sampled at the low rate increases locally the effective sampling rate and expands the bandwidth of the discrete signal.

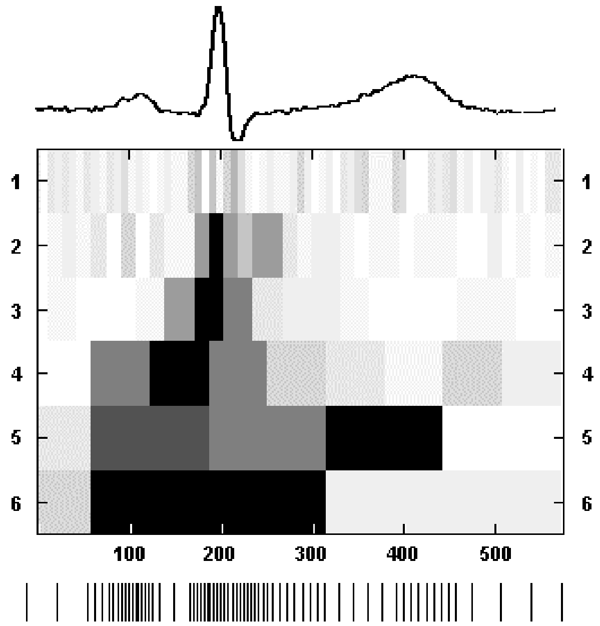

Figure 3. The ECG signal, its time-frequency representation and the effective sampling resulted from the variable depth decimation

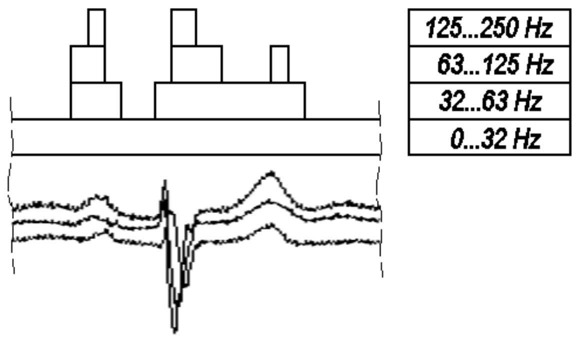

Figure 4. Coarse approximation of the ECG (0...32 Hz) and high frequency details for P, QRS and T waves

2.3. The non-uniform sampling algorithm

Sampling the signal at the variable rate involves two independent processes controlled by the adapted importance function: adjustment of the anti-alias filter's cut-off frequency and calculation of the local sampling intervals. Both of them return quantization-free values in the continuous range from the minimum to the maximum.

The role of the digital anti-alias filter in the non-uniform sampling rate algorithm is to suppress all the components falling above the local bandwidth of the ECG signal and below the Nyquist frequency of the signal sampled at the constant rate. For this purpose we adapted the sliding window average low-pass filter. The window's centre is moved to the consecutive samples of the original signal, but the window spans from 2 to 16 ms depending on the value of the adapted importance function. The border samples are partially included into the window with use of weighting coefficients, and thus the window length is not limited to the integer number of samples. The resulted cut-off frequency covers the range from 32 to 250 Hz (for sampling intervals of 16 to 2 ms).

The transformation of the constant sampling rate signal to its variable sampling rate equivalent begins with the computation of time points corresponding to irregular positions of samples (fig. 5). These positions depend on the adapted importance function (see fig. 1). Next, the continuous ECG signal is simulated from regularly spaced samples with use of cubic spline interpolation. Finally, for each irregularly spaced sample the optimized representation value is determined and memorised in the output data stream (fig. 6) [9, 10, 11].

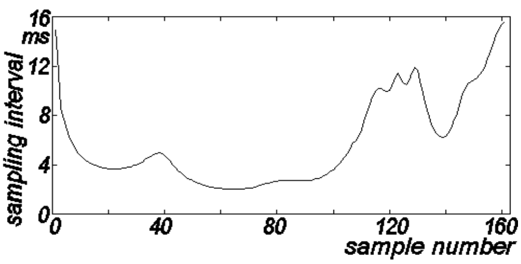

Figure 5. Sampling interval controlled by the values of adapted importance function (CSE, file Mo001)

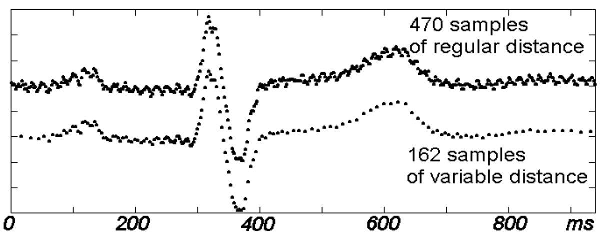

Figure 6. Comparing the heart beat represented in the regular and in the variable sampling rate signals

3. Results

For the purpose of testing, the reversible algorithm performing the variable depth decimation (VDD) was implemented in Matlab and processed the CSE-Multilead Database signals (2.44 µV, 500 Hz). The reference start- and endpoints for P, QRS and T waves in each signal were fed to the importance function adjustment procedure that provides data controlling the decimation depth. The resulted data stream volume was compared with the volume of the original record in order to compute the average compression ratio (CR). The reconstructed signal of constant sampling rate was next compared to the original signal in order to estimate the differences (PRD) caused by reduction of the data volume.

Table 1. The results of variable depth decimation - average compression ratio (CR) and differences (PRD)

CR		4.27
PRD [% (µV)]	global	4.75 (71.3)
	within P-wave borders	0.38 (5.7)
	within QRS-complex borders	0.40 (6.0)
	within T-wave borders	0.50 (7.5)
	out of waves	3.63 (54.5)

The algorithm of continuous non-uniform sampling (CNU) was also implemented in Matlab and processed the CSE-Multilead Database signals. This algorithm used the same results of importance function adjustment as the VDD procedure, but this data controls here the anti-alias filter parameters and the local sampling interval length. The average compression ratio (CR) is displayed in the table 2 together with the estimate (PRD) of global and local differences between the original and the reconstructed ECG signal.

Table 2. The results of non-uniform sampling - average compression ratio (CR) and differences (PRD)

CR		3.01
PRD [% (µV)]	global	3.11 (46.6)
	within P-wave borders	0.16 (2.4)
	within QRS-complex borders	0.22 (3.3)
	within T-wave borders	0.37 (5.6)
	out of waves	1.11 (16.6)

The results given in tables 1 and 2 confirm that the optimal discrete ECG representation is quite efficient. Our experiments considered only the aspect of data volume and distortion level, but it should be noticed that another advantage of using the adaptive sampling rate is an increase of signal-to-noise ratio. The tables also demonstrate the temporal distribution of distortions that concentrate in the signal sections with low diagnostic importance.

4. Discussion

The idea of adaptive discrete ECG representation is realized in two algorithms: variable depth decimation and continuous non-uniform sampling. The adaptability is based on the medical findings, typically used for the diagnostic purpose, derived automatically from the signal. The standard importance function represents the expected signal behavior and may be altered following the needs of particular users. The user-defined sampling profile is the third principal advantage of this approach, besides data compression and suppression of noise.

The VDD algorithm yields better efficiency and thanks to the use of LWT is significantly less complex than the CNU method. These features predestine it to the hardware implementation in portable ECG recording devices. The VDD algorithm, however, has limitations resulting from stepwise changes of sampling frequency:

- The sampling frequency is changed only by the factor of two, because of the dyadic decimation performed by the wavelet decomposition; the step of such size is far too coarse to closely follow the shape of adapted importance function.
- The temporal precision of sampling frequency adjustment is limited by the Uncertainty Principle and falls once or twice for the whole wave.
- The change of the sampling frequency results in border effect oscillations and their appearance near the wave start- or endpoints causes incorrect assessment of wave's length.

The CNU method, despite its lower efficiency, better follows the variability of physiological content of the electrocardiogram. The sampling frequency adaptation slope is smoother than in VDD algorithm and never has discontinuities that reach the limits of Uncertainty Principle. The border effect oscillations were not observed in the reconstructed signals and the diagnostic parameters computed from the optimized discrete representation were practically the same as from the original signal.

On the other hand, the efficiency and the computational complexity of the CNU method is comparable to the currently best ECG-dedicated bit-accurate compression algorithms [12]. Therefore only two advantages support the use of the CNU: suppression of noise and the user-defined sampling profile. The standard importance function is based on the physiological sequence of heart activity. In case of severe pathology, this sequence may be disturbed by extrasystolies or missing waves. Complex signal irregularities without a regular waveform (i.e. atrial flutter) do not influence the sampling rate adjustment and may cause inappropriate results of optimization. This issue needs further study before the clinical application of the adaptive discrete ECG representation.

Acknowledgements

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