Frequency Band Dependent Quantization Level for Adaptive ECG-Dedicated Signal Compression

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Abstract

The paper is devoted to the ECG-dedicated compression algorithm based on the event-driven variable quantization level in three upper octaves of the time-frequency signal representation. The algorithm uses an integer-to-integer reversible wavelet transform and the segmentation procedure developed for diagnostic purpose. Our method was implemented in Matlab and tested against the world-standard databases. Although the global compression efficiency and distortion ratio are not outstanding comparing to other compression methods, the main advantage of our method is the concentration of distortions out of the medically most important areas. For this reason, from the medical point of view, our method guarantees high fidelity of reconstructed signal and, in consequence, high reliability of signal-derived diagnostic parameters. The other advantage is that the algorithm uses integer-represented values only, that simplifies the implementation in a clinical-use real-time recorder.

1. Introduction

1.1. Motivation

One of general assumptions on every signal analysis is the possible occurrence of any probable signal component at any time, hence full bandwidth of the transmission channel is to be provided continuously. This approach guarantees time-invariant parameters of the channel throughput and thus the transmission features, such as distortions, are related to the amplitude and frequency characteristics of input signal components and not to their occurrence in time. This approach is widely used for its generality and careless use of technical resources, however is far from being efficient [1].

Fortunately, the ECG signal has several properties that may be important when considering the optimization of data stream:

- Some extend of regularity may be anticipated, even in case of serious heart diseases and some co-occurrences of signal components are impossible for the physiological reasons.
- The full bandwidth is used for short time intervals only (i. e. the QRS complex) and for a considerable amount of time the local bandwidth is much lower.
- The density of medical information is distributed not equally in the signal that makes some parts more important than the remaining sections – this medical point of view converges with the technical notion of information throughput expressed by the local bandwidth.
- The ECG signal may be segmented automatically with high reliability as it is done for the diagnostic purpose by commercially available software – the local signal properties highly correlate with the waves start- and endpoints.

These interesting properties of the ECG signal motivated us to design of an ECG-dedicated compression algorithm that would expectantly be more efficient than many general-purpose data reduction techniques widely applied in electrocardiography today.

1.2. Data reduction domains

Accordingly to the performed function, data reduction techniques may be usually classified as [2]:

- Direct methods – the samples of the original signal are subject to manipulations resulting in lower samples count (e.g. TP, AZTEC, CORTES, SAPA and others).
- Transformation methods where after a linear transformation data reduction is performed in the new domain.
- Parameter extraction methods – some features are extracted from the signal with use of a preprocessor and coded in low bitrate stream (linear prediction, syntactic or neural network methods).

Our method belongs to the intersection of the last two groups. It starts with the ECG-specialized pattern recognition and applies pattern-dependent coding rules. Comparing to uniform regular sampling, typical for a data stream originating at the A/D converter, the effective sampling frequency (samples per second) and the quantization level (bits per sample) are subject to continuous physiology-based modifications.

1.3. Data reduction rules

The data reduction rules are worked out as a result of research into the ECG signal nature and validation of other compression methods. Some of them were published in our previous papers [3-5], and the remaining were developed by other laboratories for different signal processing applications (i.e. speech compression).

The proposed compression method consists in three stages:

- Time-domain signal segmentation that uses a P- QRS-T start and endpoints detection subroutine designed for the purpose of standard ECG diagnostics.
- Thresholding of the time-frequency domain representation that eliminates all the time-frequency coefficients (TFC) not expected at a given time point; this procedure makes use of the variable local bandwidth of an ECG [3] (fig. 1).
- TFC coding at the time and frequency dependent quantization level, usually equal to, but sometimes coarser than the original samples. This procedure uses the time-variable importance of signal in the diagnostic aspect, and allows some extend of distortions for the less important parts of signal, while the more important parts are maintained unchanged [4] (fig. 2). The variable quantization level reflects also the dynamic range variability of TFC [5] (fig. 3).

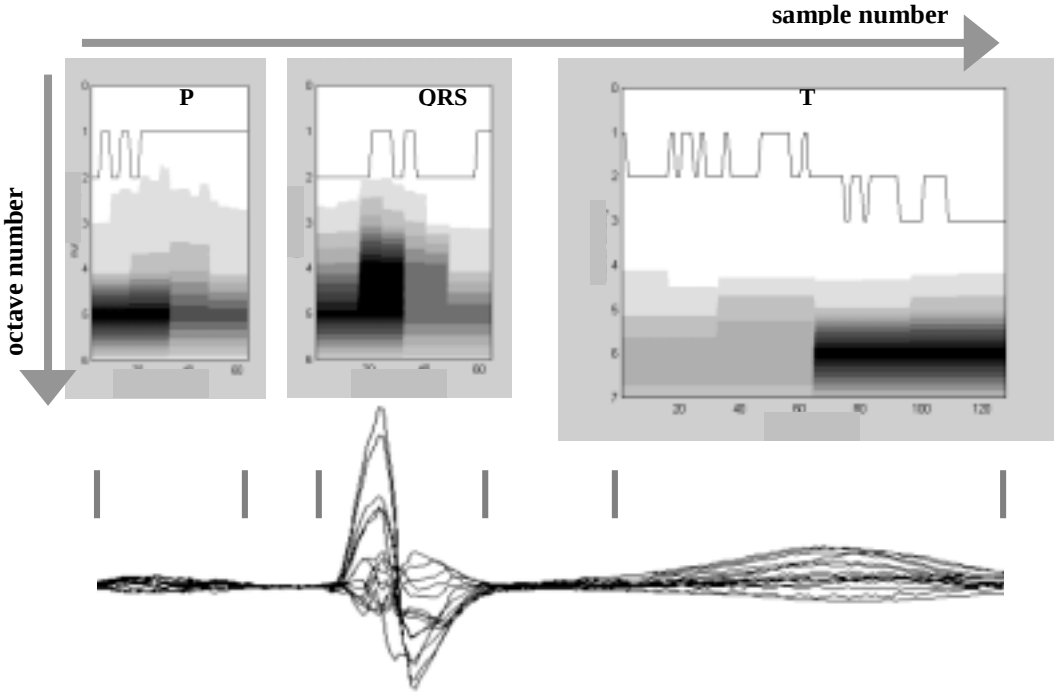

Figure 1. Averaged normalized time-frequency planes (db5 wavelets) of main components of heartbeat along with multilead signal in time domain; black lines separate coefficients representing less than 5% of instantaneous energy; sampling frequency is here 500 Hz.

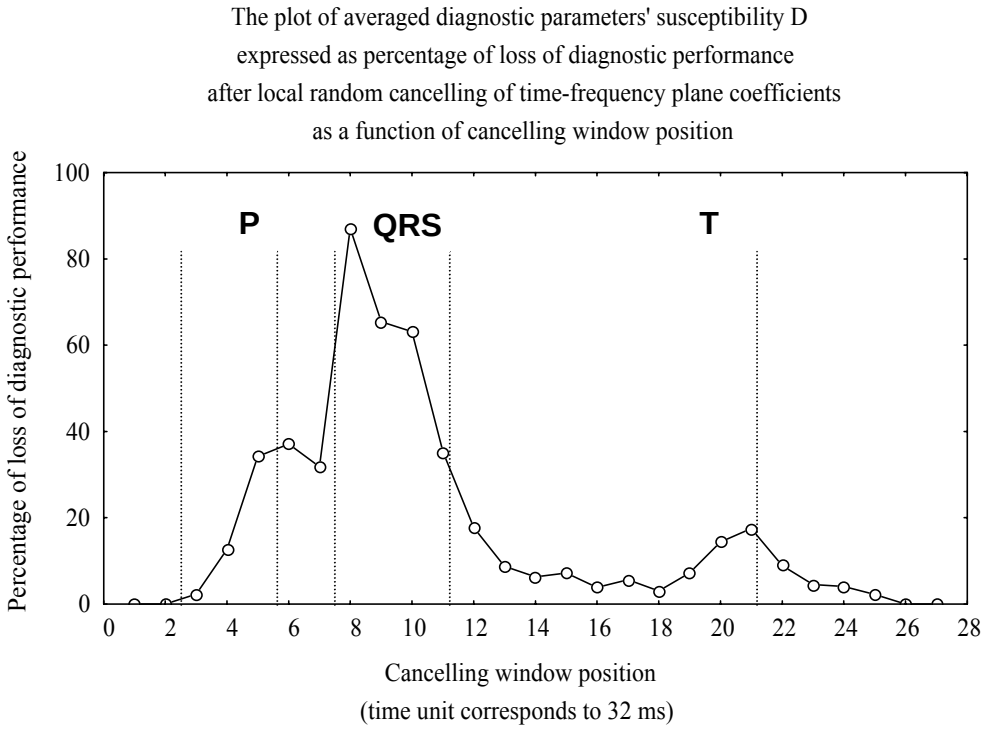

Figure 2. The function of diagnostic parameters' susceptibility to distortion caused by local random canceling of time-frequency coefficients. Additionally average wave borders are marked.

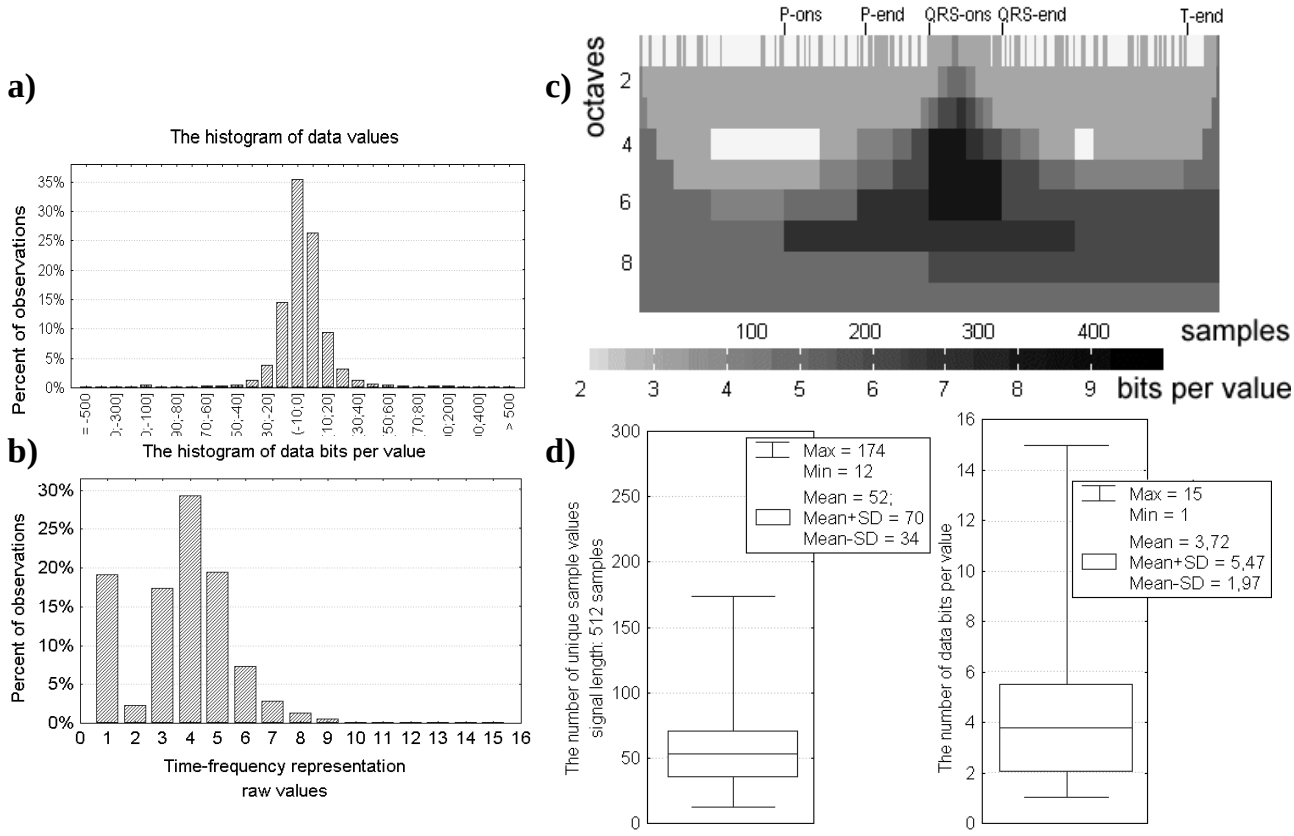

Figure 3. Dynamics of raw time-frequency ECG representations: a) histogram of values, b) histogram of bits per value representation, c) bits per value density distribution d) unique values and bits per value statistic properties

1.4. Reliability of medical information

Since we attempt to manipulate the contents of a signal that may be life-critical, special attention must be paid to the distortion checking procedures:

- inverse time-frequency transform;
- quasi-continuous time-frequency domain noise model.

Each step of data contents modification is immediately followed by comparison of the modified time-frequency representation to its original version. The compression parameters are adjusted if the given distortion ratio is close to be exceed. Additionally, the signal quality is verified in an instantaneous way beat to beat, by measuring the frequency contents at the baseline level. This measurement updates the quasi-continuous model of the ECG-noise and modifies the assumptions of the local bandwidth. For this reason, a particular TFC that is not expected at the given coordinates of the time-frequency plane, may nonetheless be preserved as an essential part of signal, if it is significantly greater than the corresponding estimated noise level.

2. Designing and testing the compression algorithm

This chapter is devoted to the technical details of the newly proposed ECG-dedicated compression method. The description of the numerical experiment carried out for testing its performance is concerned in the last paragraph.

2.1. Segmentation procedure

The ECG signal segmentation may be performed by any subroutine, but for the reasons of reliability it is important to use the software complying with the diagnostic standards. In our experiment we used an external executable subroutine developed by commercial ECG equipment manufacturer. Since three years this procedure is implemented into a family of stand-alone automatic 12-lead recorders and received wide recognition in the medical world. It was also tested for accuracy against the CSE 12-leads Database [6] and achieved the following positions in the ranking of 20 ECG and VCG reference results:

7-th for T-end delimitation accuracy;
6-th for P-onset and P-end delimitation accuracy;
5-th for QRS-onset and QRS-end delimitation accuracy.

For the purpose of compression testing, the segmentation procedure was used as a black box without any insight. The input data was a single lead continuous ECG signal, and the output data was the set of five segmentation points for each recognized heartbeat as described above. For the part of tests using the CSE Database, the segmentation procedure is not needed at all, since the database issues the reference segmentation points.

2.2. Time-frequency transform

Since the variability of the information density in an electrocardiogram is a time-domain function, the signal segmentation is performed in the time domain. On the other hand, variable amount of the data is expressed as instantaneous frequency or local bandwidth. Considering the above implies the time-frequency domain to be the most suitable for time-dependent modifications of bandwidth-variable signal coding. The time-frequency transform, that is necessary to represent the data equivalently in the time and time-frequency domains, has to meet the following requirements:

- the perfect reconstruction property;
- integer representation of signals in both domains.

Although many time-frequency transforms were published in the past and quite a big choice of them feature the perfect reconstruction property (they are also called ”reversible”) [7], the use of a transform that map integer time-domain signal to the integer time-frequency domain representation is not very common yet. Paradoxically, the use of integer representation is actually the fundamental assumption of many recent data reduction techniques and, in principle, the essential of the variable quantization level coding. Similarly, when TFC are subject to compression, they have to be represented by integer values. The use of a floating-point transform causes the real time-frequency representation and hence the unavoidable quantization issues the round-off errors. Aiming at designing of a lossless compression, or at least preserving the perfect reconstruction property of the transform step, implies the mandatory use of an integer-to-integer time-frequency transform. Our choice is the lifted wavelet transform [8] fulfilling both the requirements above.

The single stage of lifted wavelet signal decomposition (fig. 4) 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.

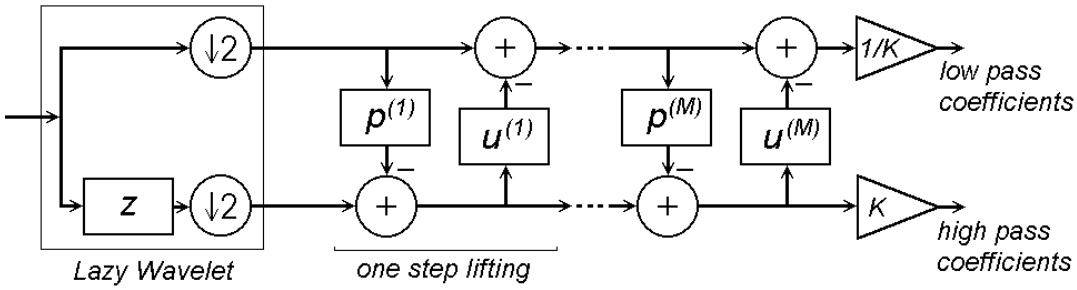

Figure 4. Computing scheme for the one stage of forward wavelet transform using *M* lifting steps

The Lazy Wavelet splits the signal into two strings:

$$\begin{aligned} s_{1,l}^{(0)} &= s_{1,2l} && \text{first, containing only even samples} \\ d_{1,l}^{(0)} &= s_{1,2l+1} && \text{second, containing only odd samples} \end{aligned} \tag{1}$$

A dual lifting step, despite the name used first, consists of applying a low-pass integer filter p to the even samples and subtracting the results from the corresponding odd samples:

$$d_{1,l}^{(i)} = d_{1,l}^{(i-1)} - \sum_k p_k^{(i)} \cdot s_{1,l-k}^{(i-1)} \tag{2}$$

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:

$$s_{1,l}^{(i)} = s_{1,l}^{(i-1)} - \sum_k u_k^{(i)} \cdot d_{1,l-k}^{(i)} \tag{3}$$

After M lifting steps, the even samples become the low-pass coefficients and the odd samples become high-pass coefficients, with applying the scaling coefficient K:

$$\begin{aligned} s_{1,l} &= \frac{1}{K} \cdot s_{1,l}^{(M)} \\ d_{1,l} &= K \cdot d_{1,l}^{(M)} \end{aligned} \tag{4}$$

In our application, we used the simplest Haar filters for p and u. The first difference acts as high-pass filter, and the average acts as low-pass filter:

$$\begin{aligned} d_{1,l} &= s_{0,2l+1} - s_{0,2l} \\ s_{1,l} &= \frac{1}{2}(s_{0,2l} + s_{0,2l+1}) \end{aligned} \tag{5}$$

It is worth a remark, that the lifting algorithm generates two subsampled strings: the decimated low-pass coarse signal and the detail high-pass signal, exactly like one decomposition stage of a traditional wavelet transform. The lifting scheme is a reversible process; thus the resulting stings contain complete original information. Thanks to perfect reconstruction property, it corresponds to reversible wavelet decomposition. The whole processing involves the integer-format values

only. For the average, the result is rounding towards -∞ or +∞, depending on the difference's least significant bit, since the sum and difference of two integers may only be even or odd both.

2.3. Components of the compressed signal

Having considered all the results of the detailed study on instantaneous bandwidth of an ECG [3] and the vulnerability of diagnostic parameters' quality to distortions induced locally on the time-frequency plane [4], we decided to split the ECG signal into two components (fig.5):

- Coarse approximation (CA) being a continuous low-frequency time-domain signal.
- Separate details (SD) being the complementary information added locally when the extended signal bandwidth is required.

This approach has several advantages:

- The CA component is a continuous time-domain signal containing all fundamental features of the ECG with the effective sampling rate of 32 Hz. If the SD component is lost due to processing errors, computing the heart rate or distinguishing the morphology of Supraventricular and Ventricular beats is still possible relying on the CA component alone.
- The CA component is ready for displaying and when only a general insight is required (i. e. monitoring in an ICU), no further processing for decomposition is necessary.
- The CA component is not compressed and thus perfectly distortion-free – some data reduction techniques were considered also for CA component, but they were given up as result of poor compression effectiveness.
- The SD component is not continuous that gives the opportunity for individual adjustment of the amplitude discretization scale adaptively to the local signal properties.
- The SD component is computed only for short sections of the signal, that is automatically detected during segmentation – usually in an ECG: P, QRS and T waves.

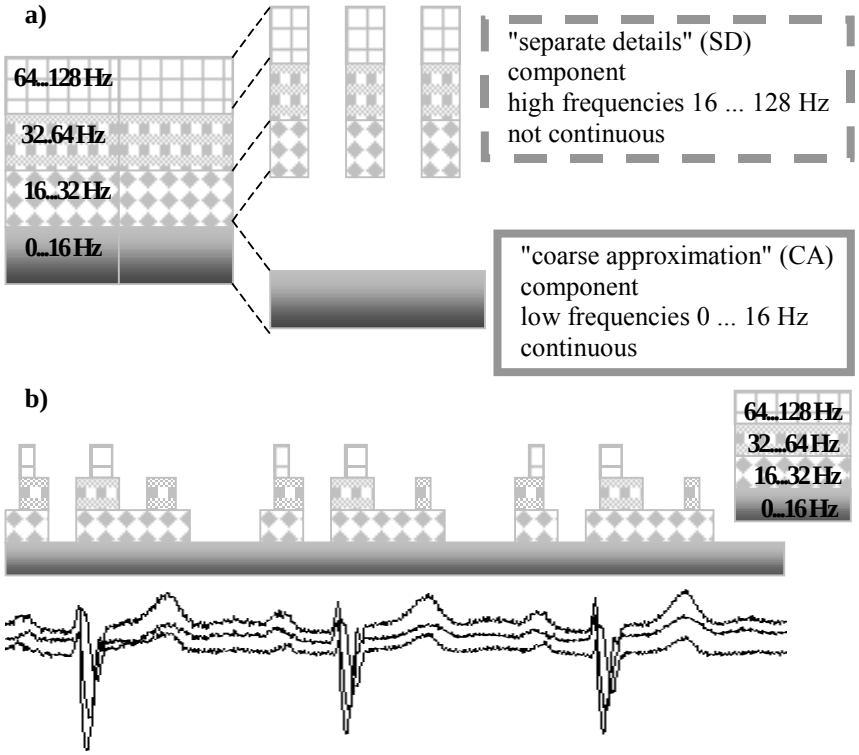

Figure 5 Splitting the ECG signals into two components: coarse approximation (CA) and separate details (SD). a) – the principle of splitting, b) – the components' behavior for an example real signal

On the other hand some properties of the assumed separation of time-frequency plane may be seen as drawbacks:

- Adaptively adjusted discretization of the amplitude needs the storage of scale coefficients with each SD component.
- Discontinuity of SD component needs the storage of synchronization points that are references to the CA signal.

- Since the time-domain resolution of time-frequency representation is coarse, in particular for the lowest SD octave, the SD duration must be span enough to overlap the considered segment of signal. This affects the effectiveness of compression, because the SD component is always longer than the corresponding section of the ECG.
- The SD component concept relies on the automatic segmentation of the signal that may fail, even when sophisticated high performance algorithms are involved, in case of interference of various origin.
- This method is limited to use with the ECG signals only, however the idea of segmentation may be extended to other variable-bandwidth signals.

2.4. Variable quantization level

Previous study on the SD components carried out in our laboratory resulted in determining of the average dynamic range for the three upper octaves (frequencies 16 – 128 Hz) of integer time-frequency ECG representation [5] (fig. 3). With respect to the original 12-bit quantization level, only few bits are needed to represent the high frequency SD components. Let *N* be a quantization level corresponding to *n* bits. For a TFC value that would need higher quantization level than *N* the probability *p* of occurrence is displayed in the Table 1.

The dyadic structure of the time-frequency plane implies that three-octaves-wide SD component should be build at least of:

- one time-frequency coefficient for the III-rd octave,
- two time-frequency coefficients for the II-nd octave,
- four time-frequency coefficients for the I-st octave.

Table 1. Probability *p* of occurrence for a time-frequency representation value that cannot be represented at the given quantization level *N*. All values result from statistical processing of the CSE-Multilead Database reference heartbeats' time-frequency representation.

quantization level *N* [*n* bits]	octaves *s* (frequency ranges)		
	I (64...128 Hz)	II (32...64 Hz)	III (16...32 Hz)
2	21.4		
3	3.9		
4	1.7	17.2	
5	0.73	4.8	
6	0.14	2.7	16.4
7		1.3	5.7
8		0.61	3.1
9			1.2

These 7 time-frequency coefficients corresponding to the frequency range of 16-128 Hz and to 32 ms of signal duration are the least separable portion of information and called the "atom" of SD component (fig. 6).

Considering the above and the results of previous research (table 1) we found the following quantization levels the most reasonable for particular octaves:

- 3 bits for each of four time-frequency coefficients in the I-st octave,
- 6 bits for each of two time-frequency coefficients in the II-nd octave,
- 8 bits for the unique time-frequency coefficient in the III-rd octave.

The total amount of bits in the SD component atom is 32, that means the complementing high frequency information lasting for 32 ms is stored in one double-word integer and corresponds to sampling interval of CA continuous signal.

The theoretical bitrate of compressed signal is a sum of the CA component constant bitrate (384 bps) and the SD component variable bitrate. To estimate the SD component bitrate we considered the average beat from the CSE Database with the following properties:

- duration of the RR interval: 886 ms
- duration of the P wave: 112 ms
- duration of the QRS complex: 109 ms
- duration of the T wave 292 ms
- the total duration of all waves: 513 ms

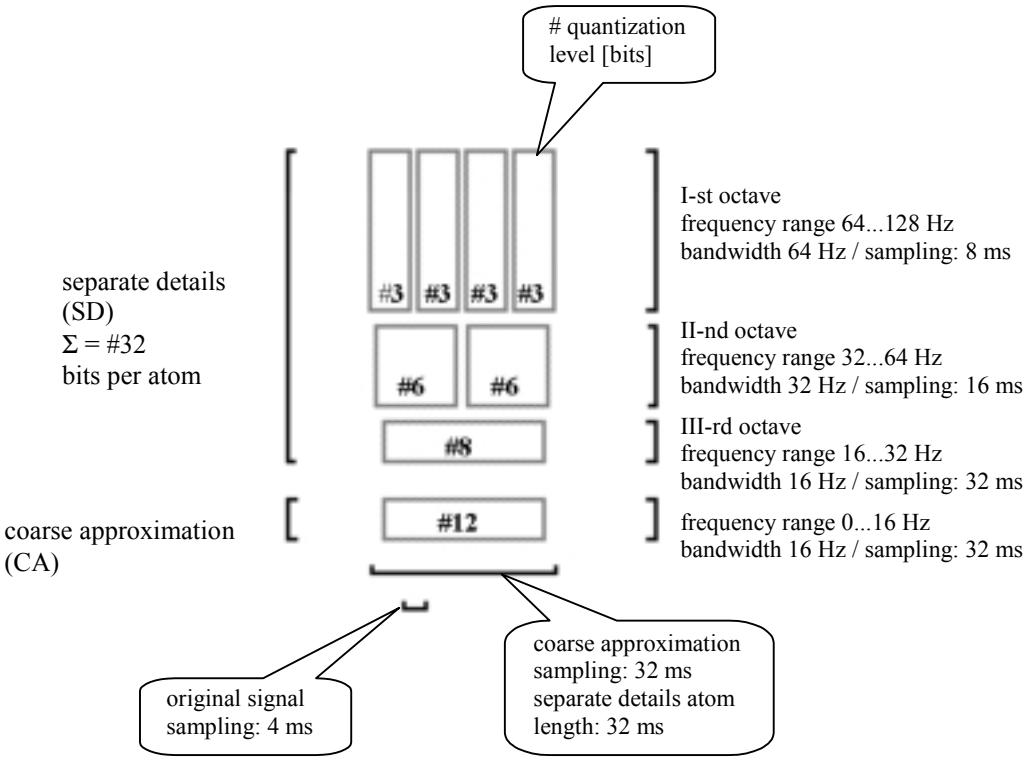

Figure 6. Description of contents and quantization levels of an ”atom” of SD component and corresponding CA component

The expected total count of SD atoms is 16, plus one byte for synchronization and three scaling bytes, that corresponds to 64 bytes per heartbeat or 578 bps. Comparing this value (384 + 578 = 962) to the original signal bitrate (3000 bps) results in compression ratio equal to 3.12.

As far as the TFC fall in the assumed dynamic range, that is true for about 96% of cases, there is no source of distortion in our compression algorithm. The remaining 4% are coefficients exceeding the expected dynamic range, that need to be re-scaled before being stored at a given quantization level. The new dynamic range is adapted for all SD atoms in the particular heartbeat accordingly to the most outstanding coefficient in each frequency band separately. The appropriate information is stored in the leading scaling byte and makes possible to restore the original coefficient value during the decompression.

Unfortunately, this new amplitude scale is coarser than the original and, in consequence, re-scaling is a lossy process due to the round-off error. The extent to that the re-scaling affects the signal quality depends on the re-scaling factor. The worst-case study for each frequency range is summarized in the table 2.

Table 2. Worst-case values of scaling factor and round-off error at assumed quantization levels

	octaves *s* (frequency ranges)		
	I (64...128 Hz)	II (32...64 Hz)	III (16...32 Hz)
maximum value of scaling factor	12 / 3 = 4	12 / 6 = 2	12 / 8 = 1.5
maximum round-off error as a percentage to full range	12.5	1.6	0.4

The rather high values of possible errors in Table 2 were calculated with the assumption that the original signals dynamic range (i. e. 12 bit quantization) is represented in a single frequency range. For a real signal, however, it is very improbable to have a maximum concentration of energy in the highest octave only. For the ECG signals, the real compression ratio and PRD distortion measure were verified by the numerical experiment.

2.5. Numerical verification of compression properties

Numerical verification of the compression algorithms features was coded and carried out in Matlab 5, except for the segmentation procedure that was available as an external executable file only. At the first stage of experiment we used the CSE-Multilead Database [9] (data set 3) providing a set of 125 recordings containing simultaneous 12-lead ECG + XYZ VCG accompanied with P-QRS-T segmentation points. The amplitude resolution is 12 bits and sampling frequency is 500 Hz. From each file the segment containing data for one heart evolution was extracted accordingly to the start- and endpoint from the database. The existence of reference segmentation points does not involve the segmentation procedure and makes the results not dependent on segmentation quality. At the second stage the MIT-BIH Database [10] was used providing two-lead signals sampled at 360 Hz. This database contains long signals with the noise and distortions of different origin. During the experiment, all available traces were segmented, compressed and decompressed as if they were separate signals. Although the Percent Root-mean-square Difference (PRD) does not assume the local variability of signal importance [11], we kept using it for the comparative purpose.

$$PRD = \left\{ \frac{\sum_{i=1}^{n} [x_1(i) - x_2(i)]^2}{\sum_{i=1}^{n} [x_1(i)]^2} \right\}^{\frac{1}{2}} \cdot 100\% \qquad (6)$$

Additional error measure, much more adequate in our opinion is the PRD value computed for each segment of signal separately. This modification reflects the local variability of signal importance and was the most straightforward when segmentation was already done by compression procedure. Similar approach is already in use in vectocardiography to express the spatial dissimilarity of the VCG-loops with means of mean quadratic difference (MQD) [12].

3. Results of the numerical experiment

The numerical experiment was carried out in two steps as described in section 2.5. The results for CSE Database are "independent" since the database provides all segmentation points and the segmentation procedure did not affect the results. Unfortunately, the processing for CSE Database is limited to one hearts evolution only which is annotated as a "reference beat". Thanks to simultaneous multilead recording, we can process all traces of the ECG signal as if they were independent, although having common segmentation points. All data reported in Table 3 as a result for a particular CSE file, is in fact a mean value of these 15 traces. The only exception is the last column that displays the sum of all cases where re-scaling was applied due to the under-estimated TFC dynamic range.

Table 3. Results for CSE Database files (distortions in %)

CSE-ID	compression ratio	total distortion	P-wave distortion	QRS-wave distortion	T-wave distortion	extra-wave distortion	re-scaling count
1	3.6132	3.5871	0.3273	0.3351	0.4443	2.3226	1
2	2.8996	1.6688	0.2270	0.3615	0.4321	1.1833	0
3	3.2676	6.2218	1.2060	1.0147	1.1487	4.1033	0
4	3.9375	4.2162	0.3577	0.3144	0.3810	2.7979	2
123	4.3224	3.3980	0.2499	0.3225	0.2650	1.8455	0
124	4.5840	2.7566	0.2602	0.4024	0.2613	1.0076	1
125	4.0652	5.5942	0.3888	0.2975	0.2645	3.0423	0
mean value	**4.2666**	**4.7463**	**0.3816**	**0.4028**	**0.4990**	**3.6303**	-
max value	8.8867	20.485	1.4572	1.0839	2.3704	15.938	-
sum	-	-	-	-	-	-	61 (3.3%)

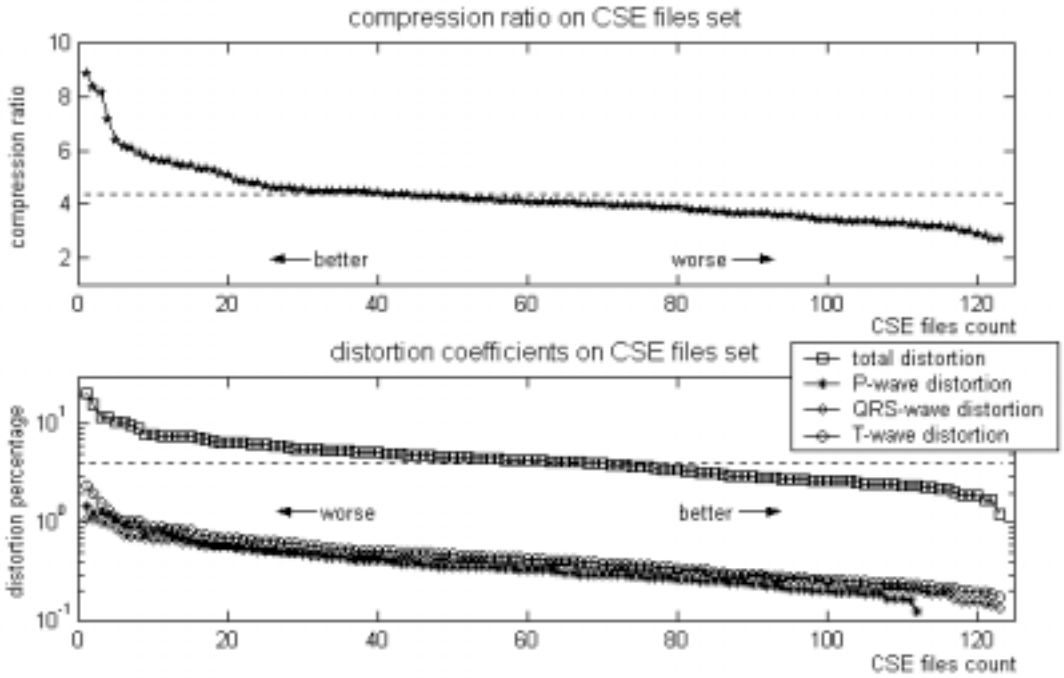

Figure 7. Compression ratios (upper part) and distortion coefficients (lower part) on CSE files set.

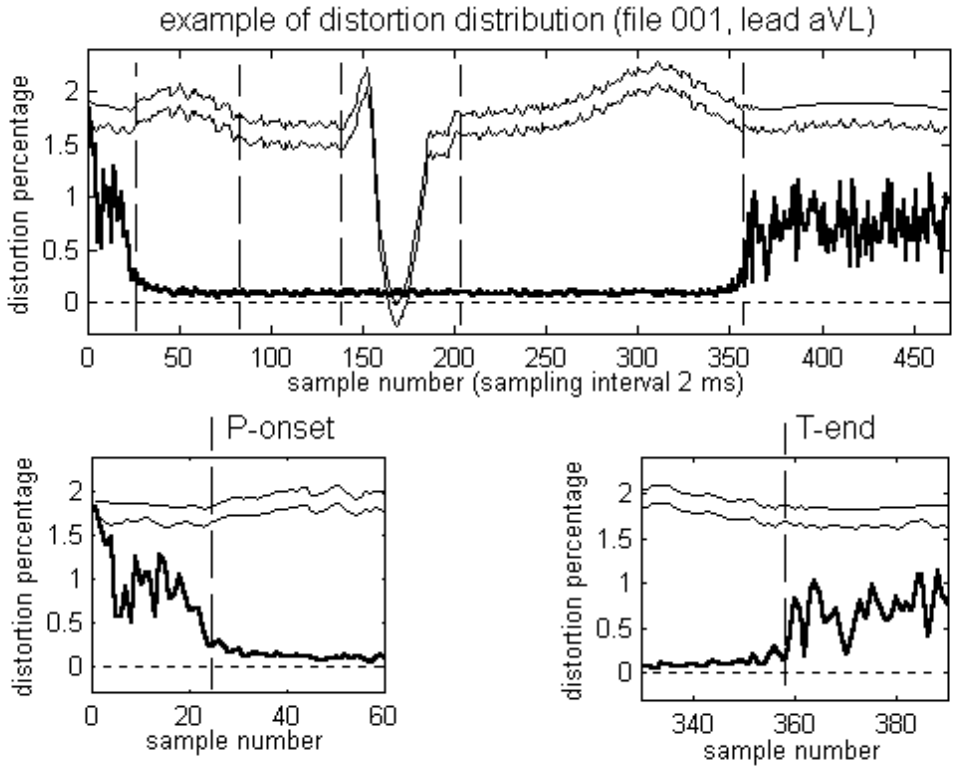

Figure 8. Example of temporal distortions distribution for the CSE-001 signal along with the lead aVL reconstructed (the top-first) and original (the top-second) traces. Below two detailed views focused on the P-onset neighborhood and T-end neighborhood. Note that the vertical axes' values apply to distortion plots only.

Figure 7 displays compression ratios and distortion coefficients for all CSE files sorted in descending order. Note that all plots are visible because of logarithmic distortion percentage scale.

Figure 8 displays an example of distortion distribution in time for the CSE-001 signal along with the lead aVL reconstructed and original traces. This plot explains the main advantage of our compression method. Even if the total distortion percentage is relatively high, the concentration of distortions falls out of the P, QRS and T waves. The physiologically controlled temporal distortion's distribution is a new aspect in biomedical signal compression. Depending on the local signal features, the process is segmentary lossless and has to be designed as signal-specific. As the essential part of the signal remains unaffected, our compression method is locally equivalent to a lossless compression. Consequently, it preserves all medical features of the ECG signal, since all the quantitative data are measured inside the P-onset to T-end zone.

Similar results were obtained with use of MIT-BIH Database. In this case, however, 44 half-hour recordings had to be pre-processed in order to find the segmentation points. Additional checking was necessary to eliminate segmentation failures or waves mismatching. All results summarized in Table 4 are averaged for all heartbeats found in both considered traces.

Table 4. Results for MIT Database files (distortions in %)

MIT-ID	compression ratio	total distortion	P-wave distortion	QRS distortion	T-wave distortion	extra-wave distortion	preprocessor failures	
							false detection	wave mismatch
100	2.4172	3.5227	0.6253	0.5121	0.6433	1.7420	0	0
101	2.9036	3.3681	0.4200	0.6115	0.5371	1.7995	1	0
102	2.7246	5.2272	0.9861	1.1077	1.3748	1.7586	3	1
103	3.7321	3.2462	0.7332	0.3247	0.4110	1.7773	0	0
232	3.3476	4.3850	0.1310	0.3573	0.3690	3.5277	7	2
233	2.7830	3.6654	0.2300	0.4244	0.3113	2.6997	0	0
234	4.1217	5.2951	0.4871	0.3897	0.4615	3.9568	1	1
mean value	**3.7191**	**4.9477**	**0.5118**	**0.4655**	**0.5899**	**4.2321**		
max value	9.5871	24.533	1.5712	1.2807	1.7389	19.852		
sum	-	-	-	-	-	-	178	24

4. Discussion

Evaluating the efficiency of newly proposed compression method we found the values of **4.2666** for CSE and **3.7191** for MIT databases, both being slightly better than theoretical value 3.12. The reason is that for theoretical estimations the only considered beats were supraventricular, while the ventricular beats due to absence of P-wave are almost 200 ms shorter than expected. In this case not only P-wave is absent, but also the P-Q segment is coded as CA component only that economizes up to 11 SD atoms. Like for most other compression methods, the effective compression ratio depends on signal contents.

The total distortion percentage is similar to values resulting from other published compression method, but the most important here is the non-uniform temporal distribution of distortions (fig. 8). The crucial part of recording, falling between the P-onset and T-end points is almost perfectly recovered from compression. The distortion level of 0.5 % of the peak-to-peak signal value (that corresponds to 10 μV) is very low and can be neglected for most clinical applications.

The origin of this error is:

- Re-scaling of high frequency octaves dynamic ranges performed occasionally in 3.3% of beats that dynamic range exceeds the expected value.
- Border effects in the neighborhood of P-onset and T-end points – other segmentation points do not affect the transformation domain's throughput and thus no border effect occurs around them.
- Smooth slope of wavelet filters that, in spite of orthogonality, do not separate the frequency band perfectly for any reasonable count of lifting step. Little energy of low frequency components is also represented in higher octaves that are modified during compression.

The results for MIT recordings are slightly inferior to the results for CSE signals. The main reason is poorer signal quality and lower original sampling frequency. Another reason is the occurrence of some segmentation errors found after

manual inspection of all recordings. Some recordings contain signals that differ significantly from the assumed P-QRS-T sequence: ventricular tachycardia (file 207), pacemaker induced beats (file 102), and many others. For those signals the compression ratio may be better than the average at a price of higher distortion level.

The medical suggestions of perfect signal reconstruction is fulfilled for the essential part of every heartbeat that is P-onset to T-end section. Due to extremely low distortions our method may be an interesting alternative to the truly lossless algorithms thanks to higher efficiency. Very few medical application areas need better accuracy than 10 μV, and even if the resolution at discretization is higher, the noise and electromagnetic interference's level exceeds usually this value. Since all the medically important features are extracted from the P-onset to T-end section, we keep a motivated belief that our compression algorithm does not change the medical data.

Another feature being worth a comment is that the algorithm uses only integer representation of the signal. From a DSP-programmers' standpoint this is an important advantage. The implementation can thus be easy and time-effective nevertheless the wavelet transform is performed. The compressed signal may be managed by any computer system based on a 32-bit word length. The continuous CA signal is stored in its original discretization level and thus the contents of frequency below 16 Hz remain unchanged by compression procedure, and thus error-free. The SD components are stored in a database as strings of SD atoms of length of 32 bits each. The database contains also synchronization points referring to the corresponding CA signal sampling points and when necessary a scaling coefficient. During the further work we plan to implement the compression procedure into a DSP-based real-time standalone 12-leads ECG recorder.

Considering the application of our compression method in the real-world electrodiagnostic equipment we have to take into account all possible behavior of the software. The main advantage of the compression method bases on the automatic segmentation that is in fact recognition of some signal features. Using a recognition procedure, that is not the topic of this paper, makes the compression algorithm "physiology-adapted" and "ECG-dedicated".

On the other hand, all that happens with the signal being compressed relies on the information provided by segmentation. For the reason of maximum reliability, we used the clinically verified subroutine for this purpose. Nevertheless, some errors were discovered thanks to manual reviewing of the processed MIT recordings. This may not only affect the compression parameters, but also may alter the medical content of the signal:

- In case of false positive detection of a wave, some part of signal is unnecessarily coded as a SD component that results in lower compression efficiency, but the medical content remains untouched.
- In case of false negative detection of a wave, the corresponding SD component is missing and the signal of P-QRS-T waves is available in simplified version only. The fundamental medical data (R-wave peak position and QRS morphology) can still be recovered using mathematical tools, therefore the computation of HRV or arrhythmia events detection is unaffected by this error. Many other data like ST-segment or QT-segment diagnostics are derived from beat-averaged templates that are not sensitive to isolated errors. The worst cases are wave segmentation or computation of late potentials' parameters that most likely fail if performed on affected heartbeat only.
- The precision of segmentation procedure does not influence the compression thanks to the size of the SD atom that spans for 32 ms in time. There is no point to recognize the wave's start- and endpoints more precisely because all points have to be moved to the nearest atom border towards the waves' outside.
- The wave mismatching does not influence the compression, since all waves are processed in the same way. In the future, we plan to differentiate the processing for P, QRS and T waves and for that application the correct recognition of wave types is necessary.

To convince the medical world to the high applicability of the frequency-band-dependent quantization level for the adaptive ECG-dedicated signal compression we plan to carry on the complementary tests on real signals. In addition to technical measures of distortion, the derived medical data should be pairwise compared and statistically processed for original signals and their reconstructed counterparts. That validation is more adapted to the medical point of view and, even in the technical world, the use of various estimators for measure the distortions in biomedical signals is widely questionable.

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