TRANSFORM-BASED REDUCTION OF INTER-CHANNEL CORRELATION APPLIED TO LOSSLESS CODING OF MULTICHANNEL ECG

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Abstract - **This work discusses the practical aspect of the transform-based decorrelation of simultaneously recorded ECG channels. High data redundancy may be observed in the conventional 12-lead ECG recordings. Eliminating this redundancy opens new possibilities for lossless coding of the ECG that complies with the most severe expectations about the signal storage. The uncorrelated signals have significantly narrower dynamic range, in result, the statistical properties featured by uncorrelated signals in the transform domain are more appropriate for various data distribution-based coding techniques (Huffman). Four linear transforms are studied and numerically verified with use of the real ECG data. Some practical considerations on the data representation format the additional overhead bits and the round-off errors complement the final result. The compression efficiency significantly exceeds the values obtained with use of general-purpose lossless algorithms.**
***Keywords* - ECG, compression, linear transform, integer wavelet decomposition.**

I. Introduction

Electrocardiogram (ECG) is the most frequently performed electrophysiological test, due to the high mortality risk of cardiovascular diseases that are induced by the life style in developed countries. For the low cost and high accessibility of the ECG, the compression of electrocardiogram signal is of great practical significance and is widely used in clinical practice. Various ECG applications usually need the compression, among of them three should be mentioned as the most important: management of databases for reference purpose, transmission of the ECG over telecommunication networks and ambulatory long term recording (Holter systems).

Several papers were devoted to reviewing and classifying of ECG-compression methods, proving the attention received by this issue in the scientific world [1], [2]. Accordingly to the performed function, data reduction techniques are commonly classified as [3]:

- 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).

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In our research we focussed on the second group of compression methods. The main goal was the exploration of performance and applicability of the perfect reconstructing compression, also called "lossless". For this purpose, the coding algorithm and the applied transforms have to be reversible in the sense of identity of the original and reconstructed discrete signal representations.

Compared to the lossy methods, lossless compression is usually featured at a price of considerably lower compression efficiency. Some diagnostic applications of the ECG, however, assume no data loss and in many countries the lossless techniques are the only legal way of medical data storage. The perfect reconstruction property may be achieved only for the finite-length sets of symbols representing the data. Each symbol is assigned a unique corresponding output token. The lossless reduction of the data volume is achieved due to the unequal probability of symbols occurrence, when the frequent symbols are represented by shorter tokens. This method is a foundation of a class of histogram-based coding techniques, characterized by variable-length output tokens, among of which the most popular is the Huffman Coding and its successors.

The lossless coding may be applied to the raw ECG data making use of the natural distribution of quantized ECG values. However, the compression efficiency increases for the narrow-histogram signals where many datapoints are represented with use of few symbols. This justifies the pursuit for a reversible transform yielding the distribution of symbols optimized for effective coding. The simplest example of such transform is time-domain differentiating.

The differentiating and its successors (short- and long-time prediction methods) were found very efficient for the single channel ECG compression [4], [5], and [6]. For multichannel signals the additional improvement of efficiency is expected because of high information redundancy in the simultaneously recorded signals. During the reported research we focussed only on transform-based channel decorrelation, but certainly this technique may be a part of a complex coding method [7], [8]. Consequently, our aim is to investigate how much memory (or data stream) can be saved by elimination of the intra-channel redundancy.

II. Methodology

As far as the perfect reconstruction is considered, all transforms are expected to yield the reconstructed signal identical to its original counterpart, that usually is fixed-point valued. Since the decorrelated signals dynamic range is very low, the round-off error, issued if the floating-point representation is used, yields an unacceptable level of distortion in the reconstructed signal.

For the redundancy, the limb channels III, aVR, aVL and aVF may be discarded at the beginning. They may be always calculated from two retained limb channels, I and II. Because of high correlation expected in the chest channels V1 ... V6, these channels are put before the limb channels in the data set. Decorrelating the multichannel signal involves the use of linear transform (1):

$$Y_n = A \cdot X_n \tag{1}$$

where $X_n = [x_1(n),..., x_C(n)]^T$ is the original domain signal representation, $Y_n = [y_1(n),..., y_C(n)]^T$ is transform domain signal representation and A is the $C \times C$ transform matrix.

The optimum linear transform, the discrete Karhunen-Loeve Transform (KLT), is defined for the stationary random processes, but it may be extended for slowly varying nonstationary processes like ECG. The transform matrix is computed from the statistics of the ECG signals. First the covariance matrix V_x is estimated from the ECG channels:

$$V_X = \frac{1}{M} \sum_{i=0}^{M-1} \begin{bmatrix} x_1(i) \\ \vdots \\ x_C(i) \end{bmatrix} \begin{bmatrix} x_1(i) & \cdots & x_C(i) \end{bmatrix} \tag{2}$$

where M is the number of ECG samples per channel and C is the channel count (eight in our case). In next step, the eigenvectors of the covariance matrix V_x are computed and used as rows of the transform matrix A.

The KLT is issued by eigenvalues decomposition and thus performs the optimal channel decorrelation. Unfortunately, its implementation requires overcoming the technical problems:

- there is no fast algorithm for KLT computation,
- the transform matrix is necessary for the signal reconstruction and has to be stored with the signal and the overhead decreases the compression performance,
- processing longer time sections lowers the overhead influence, but the assumption of "stationarity" is less acceptable,
- the transform matrix uses floating-point data representation; in order to obtain the fixed-point output, the transform involves quantization that yields round-off errors, the alternative solution is computation of fixed-point matrix A' nearest to the original A, but the computation is time consuming and the transform is no longer "optimal"

The alternative approach uses the Discrete Cosine Transform (DCT) in the role of linear transform. The transform is fed by the sequence of corresponding samples in all considered channels: $X = [x_1(i) \ \cdots \ x_C(i)]$. For this sequence, the DCT coefficients are defined as:

$$G(k) = \sqrt{\frac{\alpha_k}{C}} \sum_{s=0}^{C-1} x(s) \cdot \cos \frac{(2 \cdot s + 1) \cdot k \cdot \pi}{2 \cdot C} \tag{3}$$

where k = 0, 1, 2, ... C-1, α_k = 1 for k = 0 and α_k = 2 otherwise. The DCT is a suboptimal transform that approximates the theoretical performance of KLT. However, the computation of the DCT is more efficient than in case of KLT, there exist fast algorithms of order (N log N) performing the transform. Some specialized DSP processors provide the ability of DCT operation in the hardware. The additional advantage is the absence of transform matrix, because of the use of "standard" cosine function. The compression performance is thus not affected by the overhead.

Third option is the channel decorrelation by the differentiating of their time-frequency representation. If the decomposition performed uses real-valued orthogonal filters, the resulting time-frequency plane is also real-valued (also called: "phaseless"). An interesting property of such representation is the support of arithmetical operations on the signals as if they were performed in the time domain. The important frequency components occur in the same time in all simultaneously recorded channels that justifies the hope for lower dynamic range of the sequence containing differences of the corresponding time-frequency atoms.

The use of a floating-point transform causes the real-valued time-frequency representation and the resulting signal sampled at the variable rate is also real-valued or the additional quantization issues the round-off errors.

An interesting alternative is the use of wavelets that map integers to integers [9] [10]. For the novelty of this approach its principles are worth to be reminded hereby.

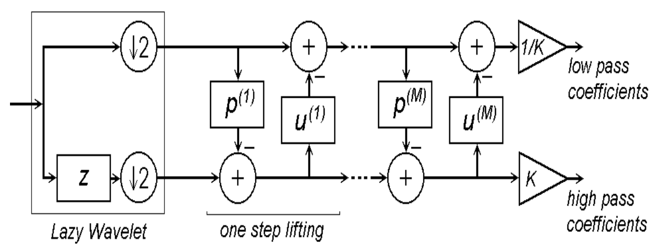

Fig. 1. The computing scheme of one stage of wavelet decomposition using M lifting steps

The single stage of lifted wavelet signal decomposition (figure 1) starts with splitting the signal into two half-length components, what is called 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.

The Lazy Wavelet splits the signal into two strings:

$$\begin{aligned} s_{1,l}^{(0)} &= s_{1,2l} \\ d_{1,l}^{(0)} &= s_{1,2l+1} \end{aligned} \tag{4}$$

first, containing only even-indexed samples
second, containing only odd-indexed samples

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:

$$d_{1,l}^{(i)} = d_{1,l}^{(i-1)} - \sum_k p_k^{(i)} \cdot s_{1,l-k}^{(i-1)} \qquad (5)$$

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:

$$s_{1,l}^{(i)} = s_{1,l}^{(i-1)} - \sum_k u_k^{(i)} \cdot d_{1,l-k}^{(i)} \qquad (6)$$

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

$$\begin{aligned} s_{1,l} &= \frac{1}{K} \cdot s_{1,l}^{(M)} \\ d_{1,l} &= K \cdot d_{1,l}^{(M)} \end{aligned} \qquad (7)$$

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:

$$\begin{aligned} d_{1,l} &= s_{0,2l+1} - s_{0,2l} \\ s_{1,l} &= \frac{1}{2}(s_{0,2l} + s_{0,2l+1}) \end{aligned} \qquad (8)$$

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.

III. Results

A. Conditions of the numerical experiment

Numerical verification of the compression algorithms features was custom-coded and carried out in Matlab 5, except for the Huffman coding procedure downloaded over the Internet [11]. As a source of multichannel ECG data we used the CSE-Multilead Database [12] (data set 3) providing a set of 125 recordings containing simultaneous 12-lead ECG and the P-QRS-T segmentation points. The amplitude resolution is 12 bits and sampling frequency is 500 Hz. We developed our own m-files for the KLT and LWT transforms accordingly to the original authors, while the DCT, and the compactly supported WT (Daubechies) were provided by Matlab. Main goal of our research is to eliminate the data redundancy aiming at the effective but lossless signal storage. For this reason the performance of decorrelation algorithms was measured as the bitrate of the data yielded by the Huffman coding performed on decorrelated data.

B. Results for the KLT overhead

The KLT, however provides the optimal decorrelation, is far from being optimal for the real-world implementation. One of reasons is the existence of the optimal matrix A (1) with the floating-point entries for each data set. For the fixed-point application two solutions are possible: searching for a sub-optimal fixed-point matrix or quantization of the optimal matrix. The second option was applied in our experiment because of avoiding very expensive computation at a price of round-off errors that appear as a low but non-zero distortion level. The contribution of the data overhead may be reduced for longer data section processed at a time. In this case, however, the stationarity condition is less fulfilled, and thus the decorrelation is no longer optimal. In the introductory part of the experiment, the percentage of the data overhead contribution and the distortion level were screened for dependence on the signal length. Table 1 and 2 summarize the results for section's durations of 0.5, 1 and 2 s.

Table 1
PERCENTAGE OF THE DATA OVERHEAD CONTRIBUTION

CSE-ID	signal length [ms]		
	500	1000	2000
1	71.8	39.7	20.5
2	67.5	37.3	20.7
124	54.6	38.7	24.0
125	55.1	39.9	23.9
mean ± std	62.3 ± 10.6	38.2 ± 4.51	20.8 ± 2.05

Table 2
DISTORTION LEVEL [PRD %] FOR VARIOUS SIGNAL LENGTH

CSE-ID	signal length [ms]		
	500	1000	2000
1	0.19	0.19	0.20
2	0.30	0.29	0.29
124	0.39	0.37	0.37
125	0.28	0.30	0.33
mean ± std	0.28 ± 0.07	0.31 ± 0.09	0.34 ± 0.09

C. *Performance of signal decorrelation*

Assessment of the transform-based decorrelation's performance uses a constant-length signal's section of 512 samples that represents on average one heartbeat interval. Table 3 displays the decorrelation performance and fig. 2 shows an example of KLT–based decorrelation. (CSE-001).

Getting a low distortion level for rounded KLT transformation matrix and DCT coefficients, we intended to apply the quantization to the time-frequency representation as well.

TABLE 3
DECORRELATION PERFORMANCE
EXPRESSED AS HUFFMAN CODING OUTPUT BITRATE (Kb/s)
ORIGINAL BITRATE 6.0 Kb/s

CSE-ID	decorrelation method				
	no transform	KLT	DCT	WT (Daub5)	LWT
1	3.66	2.80	3.45	2.38	1.51
2	3.85	2.82	3.26	2.67	1.66
124	4.12	2.53	2.51	1.94	1.16
125	4.11	2.72	2.87	2.33	1.40
mean ±std	3.85 ±0.50	2.82 ±0.32	3.10 ±0.40	2.40 ±0.27	1.49 ±0.21
PRD [%]	0	0.31	0.38	10.8	0.071

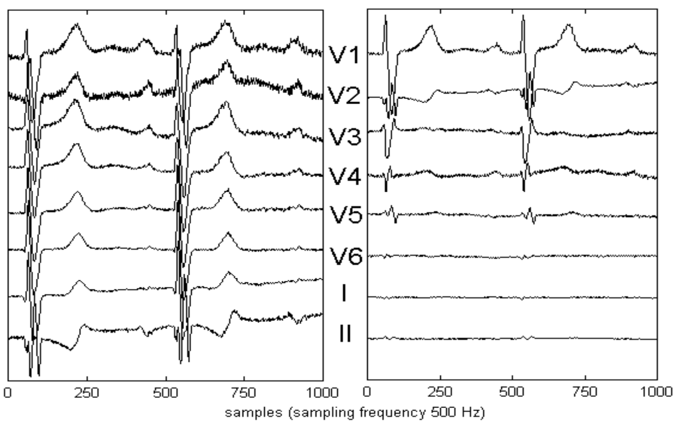

Fig. 2. Example of KLT–based decorrelation of CSE file Mo_00001

As we completed the experiment using the Daubechies 5-th order compactly supported wavelet, it turned out that the t-f coefficients are extremely vulnerable to the round-off error. In consequence, even for a perfect reconstruction transform, the distortion level exceeds the acceptable values. The source of the round-off error was eliminated by the use of LWT that in whole processing uses fixed-point data representation only.

IV. DISCUSSION

Four data decorrelation techniques were implemented and tested in course of the numerical experiment with use of the original ECG signals. The decorrelation is designed for the purpose of reducing the volume of the data stream and thus the use of fixed-point data representation is assumed for the input and output signals. Although the decorrelation technique and the subsequent Huffman coding have perfect reconstruction property, slight difference between the original and reconstructed signals caused by data round-off error appear for KLT and DCT transforms. In case of conventional WT the distortion level was surprisingly high and this method should not be considered for application unless improved. On the opposite, the application of LWT yields a practically lossless coding where the only differences appear at the end of the signal sections due to the border effect and the filter roll-off. In a target application segment overlapping may eliminate these differences.

V. CONCLUSION

Decorrelation of the multichannel ECG recordings may reduce the output data stream by a factor of 4 in case of LWT. The perfect reconstruction property is the most important feature of the decorrelation-based compression technique. Certainly, the spatial (or inter-channel) decorrelation may be combined with other time-domain techniques, like differentiating or prediction, resulting in a new lossless data compression algorithm of high efficiency. Another advantage of the spatial decorrelation is that this technique accepts raw signal at the input and all additional processing consists in getting the optimal channel's sequence. The real-world implementation should consider the existence of specialized Signal Processors performing the DCT in the hardware. The implementation of the LWT is also feasible even in a simple processor using fixed-point arithmetic.

REFERENCES

[1] J. L. Cardenas-Barrera, J. V. Lorenzo-Ginori "Mean shape vector quantizer for ECG signal compression" *IEEE Trans. Biomed. Eng.* vol. 46 pp 62-70, 1999

[2] M. Hilton "Wavelet and wavelet packet compression of eletrocardiograms" *IEEE Trans. Biomed. Eng.* vol. 44 pp 394-402, 1997

[3] S. M. S. Jalaleddine, C. G. Hutchens, R. D. Strattan, W. A. Coberly "ECG data compression techniques – a unified approach" *IEEE Trans. Biomed. Eng.* vol. 37 pp 329-343, 1990

[4] B. Bradie "Wavelet packet-based compression of single lead ECG" *IEEE Trans. Biomed. Eng.* vol. 43 pp 493-501, 1996

[5] G. Nave, A. Cohen "ECG compression using long term prediction" *IEEE Trans Biomed. Eng.* Vol. 40, 877-885, 1993

[6] B. Wang, G. Yuan "Compression of ECG data by vector quantization". *IEEE Eng. Med. Biol.* vol. 16, No 4 pp 23-26, July/Aug 1997

[7] A. Cohen, Y. Zigel "Compression of multichannel ECG through multichannel long-term prediction" *IEEE Eng. Med. Biol.* vol. 17, No 1 pp 109-115, Jan/Feb 1998

[8] A. E. Cetin, H. Koymen, M. C. Aydin "Multichannel ECG data compression by multirate signal processing and transform domain coding techniques" *IEEE Trans. Biomed. Eng.* vol. 40 pp 495-499, 1993

[9] A. R. Calderbank, I. Daubechies, W. Sweldens and B. Yeo "Wavelet transforms that map integers to integers", *technical report*, Princetown Univ., 1996

[10] L. Chen, W. Chen, S. Itoh "Lossy to lossless compression of ECG data using integer wavelet transform" *in proc. Eur. Medical & Biological Engineering Conference EMBEC'99* Nov 4-7 1999, Vienna, Austria

[11] K. Skretting, http://www.ux.his.no/~karlsk/

[12] J. L. Willems "Common standards for quantitative electrocardiography" *10-th CSE Progress Report*, 1990. Leuven: ACCO publ., 1990, 384p.