EEG DATA COMPRESSION BY MEANS OF WAVELETS TRANSFORM

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RÉSUMÉ

Le but de cet article est de proposer un EEG système de compression pour les données électro-encéphalographiques avec une perte des informations controllée. Cette technique ne permet pas une reconstruction parfaite de la forme d'onde du signal original mais elle produit un bon fonctionnement en termes de bit-rate et en plus elle n'a besoin que de peu de calculs.Le système de compression se base sur la transformation des wavelet packets, qui a eté réalisée par des bancs de filtres d'analyse. On a activé un algorithme pour ranger la distorsion dans chaque bande pour réduire l'entropie totale à la sortie du système de synthèse. On a employé UTQ quantizers pour quantifier les subband coefficients. Les niveaux de reconstruction ont été projetés pour une distorsion minimum puisque on sait que la distribution des coefficients est Laplacienne.

ABSTRACT

In this paper an EEG data compression system with a controlled loss of information is proposed. Such a technique does not allow a perfect reconstruction of the original waveform signal but produces good performances in bit-rate terms and it has also a low computational cost. The compression system is based on the wavelet packets transformation, which has been implemented through different analysis filter banks. An algorithm to allocate distortion in the single subbands has been implemented to reduce the total entropy at the output of the synthesis system. UTQ quantizers have been used to quantify the subbands' coefficients. The reconstruction levels are projected for minimum distortion knowing that the coefficients' distribution is Laplacian.

1. Introduction

EEG digital recording allows data storage on optical or magnetic media with consequent saving of physical space in comparison with usual paper recording. This is however relatively expensive if row data are stored directly. Some attempt to reduce or compress the amount of data before storage is therefore desirable. In this paper we propose a compression system with a controlled loss of information. Such a technique does not allow a perfect reconstruction of the original waveform signal but produces good performances in bit-rate terms and it has also a low computational cost. The compression system is based on the wavelet transform, a well known tool in data compression and EEG analysis.

The wavelet packets decomposition has been chosen because of its suitability for EEG analysis, in fact such a transform decomposes every frame in a set of subbands having the same number of samples, and with the same spectral width. The wavelet coefficients are obtained with recursive filtering operations, similar to subband coding schemes using QMF banks. Several filter types have been implemented considering both FIR and IIR approach. An algorithm to allocate distortion in the single subbands has been implemented to reduce the total entropy at the output of the synthesis system.

The subbands coefficients have amplitude distributions which can be approximated with Laplacian functions. This is used to realize UTQ quantizers with reconstructed levels optimized for minimum distortion. The quantified coefficients are then coded using both Huffman and run-length coding.

2. The wavelet decomposition

In the *multiresolution analysis,* proposed by Mallat [1], two functions are defined: the *scaling function* $\phi(x)$ and the *mother wavelet* $\psi(x)$. For a fixed m the set of functions $\phi_{m,n}(x) = 2^{-m/2}\phi(2^{-m}x - n)$ which are dilated and translated versions of the scaling function forms an orthonormal basis of V_m. Let V_m denote the subspace formed by the approximations of all the functions in $L^2[a,b]$ at the resolution 2^m. V_m includes all lower resolution approximations so $\ldots V_2 \subset V_1 \subset V_0 \subset V_{-1} \subset V_{-2}\ldots$ The discrete approximation of a function $f \in L^2$ is described by the coefficients $a_{m,n}(f) = \langle \phi_{m,n}, f \rangle = \int \phi_{m,n}(x) f(x)dx$ which constitute the so called *lowest approximation signal*. If the function is given in sampled form then these samples constitute the highest order resolution approximation coefficients $a_{0,n}$. The functions $\psi_{m,n}(x) = 2^{-m/2}\psi(2^{-m}x - n)$ span a space W_m which is exactly the orthonormal complement in V_{m-1} of V_m. The coefficients $d_{m,n}(f) = \langle \psi_{m,n}, f \rangle$ represent the *detail signal* and describe the information lost in the transition from an approximation of f with resolution 2^{m-1} to the coarser approximation V_m at resolution 2^m. The coefficients $a_{m,n}$ and $d_{m,n}$ can be calculated with simple digital filtering operations by:

$$a_{m,n}(f) = \sum_{k=-\infty}^{+\infty} h_{2n-k} a_{m-1,k}(f)$$
$$d_{m,n}(f) = \sum_{k=-\infty}^{+\infty} g_{2n-k} a_{m-1,k}(f) \quad (1)$$

where $g_n = (-1)^n h_{1-n}$ and $h_n = \sqrt{2} \int \phi(x-n)\phi(2x)dx$ are the filter coefficients. A reconstruction formula exists so that

$$a_{m-1,n}(f) = \sum_{k=-\infty}^{+\infty} [h_{2k-n} a_{m,k}(f) + g_{2k-n} d_{m,k}(f)] \quad (2)$$

The synthesis and the analysis filters are related by $H'(z)=H(z^{-1})$, $G'(z)=G(z^{-1})$ and $G(z)=z^{-1}H(-z^{-1})$. If piecewise polynomial wavelet functions are used then the relationships between the scaling function $\phi(x)$ and the filter H are [1]:

$$H(\omega) = \frac{[\Sigma_{2n}(\omega)]^{\frac{1}{2}}}{2^n [\Sigma_{2n}(2\omega)]^{\frac{1}{2}}} \quad (3)$$

where

$$\Sigma_n(\omega) = \sum_{k=-\infty}^{+\infty} \frac{1}{(\omega + 2k\pi)^n}$$

and $n=2p+2$ where $2p+1$ is the degree of the building polynomials.

3. Wavelet packets decomposition

The *wavelet packets decomposition* is obtained by further decomposing every subband in the transition from a finer to a coarser decomposition level. Let $w^0_{0,n}(f)$ be the approximation of a function $f \in L^2$ at the highest resolution (m=0). At the decomposition level m, 2^m subbands are obtained, all with the same spectral width and the same number of coefficients in the inner. We denote by $w^j_{m,n}(f)$ the j-th ($0 \le j < 2^m$) subband coefficients that approximate f at the resolution level m. It is possible to decompose $w^j_{m,n}(f)$ by means of digital filtering operations such that:

$$w^{2j}_{m,n}(f) = \sum_{k=-\infty}^{+\infty} h_{2n-k} w^j_{m-1,k}(f)$$
$$w^{2j+1}_{m,n}(f) = \sum_{k=-\infty}^{+\infty} g_{2n-k} w^j_{m-1,k}(f) \quad (4)$$

$j=0\ldots2^{m-1}$

The expressions (4) show that $w^j_{m-1,n}$ is subdivided in two sequences: $w^{2j}_{m,n}$ and $w^{2j+1}_{m,n}$. The first one representing the approximation of $w^j_{m-1,n}$ at the resolution level m, while the second is the *detail*, that is the information we need to reconstruct $w^j_{m-1,n}$ from $w^{2j}_{m,n}$.
The reconstruction algorithm is shown by the relation:

$$w^j_{m-1,n}(f) = \sum_{k=-\infty}^{+\infty} h_{2n-k} w^{2j}_{m,n}(f) + g_{2n-k} w^{2j+1}_{m,n}(f) \quad (5)$$

The number of multiplications to perform the wavelet packets transform with FIR filters is $M_p = mNr$, where m is the decomposition level, N is the number of signal samples, r is the number of the filter coefficients.

4. Compression systems

The compression process works on a set of samples called frame. It consists of four steps: wavelet packets transformation, distortion allocation, coefficients quantization and coding. A visual scheme of the compression system architecture is given in Fig.1.

We have implemented the wavelet packets decomposition because it can also be used with purposes related with the EEG analysis. This decomposition subdivides a frame in 2^m subbands with the same spectral width, being m the decomposition level. Thanks to the decimation process there is not redundancy so the total number of coefficients remains the same. This is important since it resolves the problem of the enormous number of coefficients when using analysis filter banks. In our tests we have found that some typical EEG graphoelements like epileptic spikes, alpha rhythm etc. are more evident in the subbands than in the original tracing.

We have used three different types of wavelet packets decompositions: in the first two the filter H is a FIR filter obtained from linear and cubic piecewise polynomial wavelets, while in the latter H has been implemented with an IIR filter derived from linear polynomial wavelets [2]. In the following we shall denote the two FIR and the IIR filters by LIN, CUB and IIR respectively.

The coefficients in the high-pass subbands are directly quantized, in fact they are sufficiently decorrelated and their distribution can be approximated with a Laplacian function. In the low-pass subband the coefficients maintain a certain correlation that we reduce by means of a DPCM scheme. A fixed distortion (MSE) at the output of the synthesis system can be imposed. It is possible to allocate this distortion in every subband in order to reduce the bit-rate [3]. Once distortion is allocated we proceed with coefficients quantization. We have used a scheme with an UTQ quantizer [4] for every subband. Thanks to the hypothesis of Laplacian distribution, it is possible to obtain the reconstruction levels in a closed form.After quantization, the coefficients are finally coded. An Huffman coder and run-length coding [5] have been used.

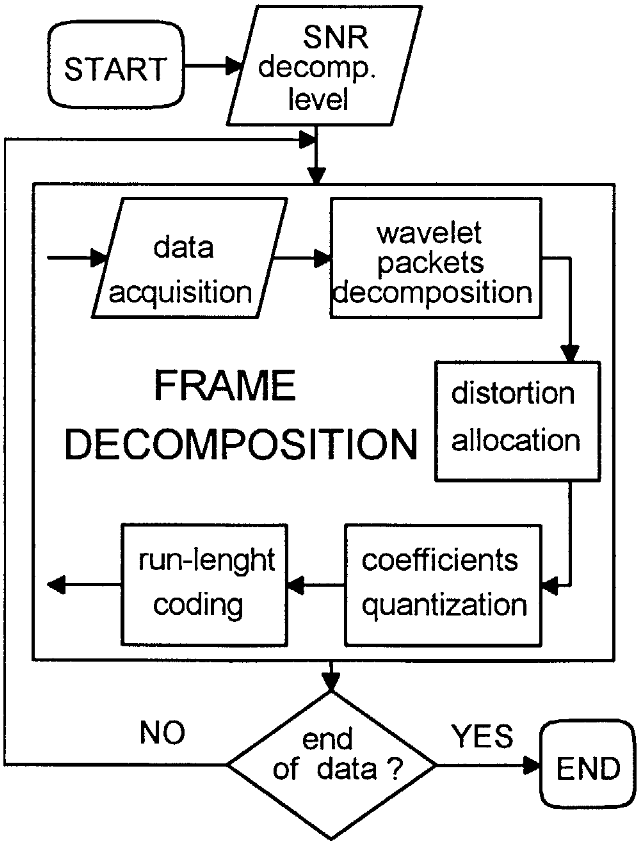

Fig.1 **Data compression system architecture.**

5. Experimental results

We have based our tests on two different recording. The first represents an EEG tracing from a normal patient while the second is recorded from an epileptic patient. Every tracing is obtained by an EEG machine (GALILEO VEGA 24 by ESAOTE BIOMEDICA S.p.A) with a 128 Hz working frequency, 8 bits per sample. In order to obtain virtual real time execution the original tracing of 25600 samples, corresponding to 3'20" of recording, has been subdivided in 10 frames of 2560 samples each, and every frame has been compressed separately.

We have implemented the compression systems on a 386DX PC-IBM compatible machine, with a clock frequency of 33 MHz and math coprocessor.

We impose a value of SNR to fix a determined distortion. SNR is calculated with the expression:

$$SNR = -10\log\left(\frac{\frac{1}{N}\sum_{i=0}^{N-1}[x(i)-x_r(i)]^2}{255^2}\right)$$

The compression performance varies with the predetermined reconstruction accuracy as it can be seen in the following tables.

	Bit-rate (bit/s)	Compression time (s)
IIR	1.65	8
LIN	1.66	12
CUB	1.56	13

Tab.1 **EEG tracing from normal patient. SNR=45 dB, decomposition level m=1.**

	Bit-rate (bit/s)	Compression time (s)
IIR	1.9963	9
LIN	1.98	13
CUB	1.8931	14

Tab.2 **EEG tracing from an epileptic patient. SNR=45, decomposition level m=1.**

	Bit-rate (bit/s)	Compression time (s)
IIR	3.45	17
LIN	3.44	20
CUB	3.32	24

Tab.3 **EEG tracing from normal patient. SNR=55 dB, decomposition level m=1.**

	Bit-rate (bit/s)	Compression time (s)
IIR	3.4038	46
LIN	3.3919	52
CUB	3.2394	59

Tab.4 **EEG tracing from normal patient. SNR=55 dB, decomposition level m=2.**

We have better performance with the normal tracing rather than with the epileptic one. This could have been expected since epileptic tracing is less correlated than normal one.
The tests with different analysis filter banks denote that the best performances in bit-rate terms are obtained with CUB filters while LIN and IIR give almost the same performance, while compression times yield the IIR banks faster than the others. However even by using the slower bank (CUB) we can see that 3'20" of recording are compressed 59" for a second level decomposition).

In the following figures we show the reconstructed waveforms in comparison with the original ones for different imposed SNR.

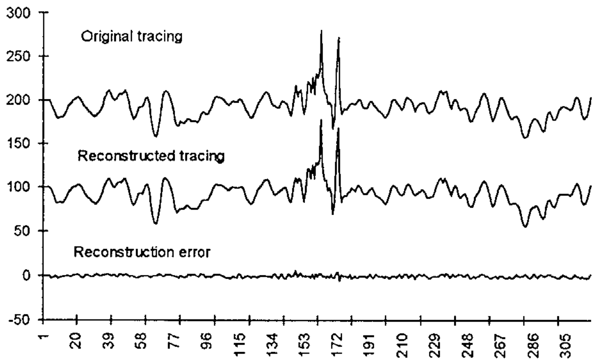

Fig.2 Reconstruction of 320 samples from epileptic tracing. CUB filters, SNR=45 dB.

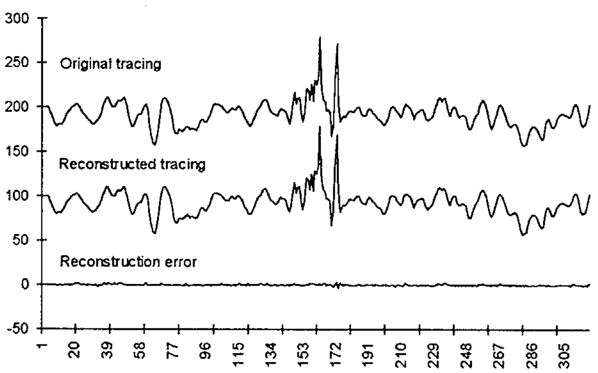

Fig.3 Reconstruction of 320 samples from epileptic tracing. CUB filters, SNR=55 dB.

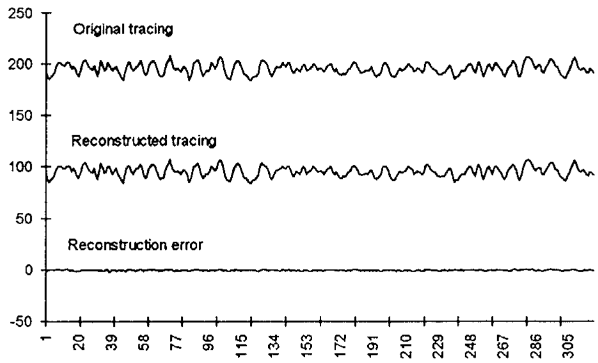

Fig.4 Reconstruction of 320 samples from normal tracing. CUB filters, SNR=55 dB.

6. Conclusions

In this work a system for EEG data compression based on the wavelet packets transform has been presented. Three different banks has been used. The bank denoted as CUB has given the best results in terms of compression ratio and acceptable performance in terms of computational cost.

References

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