BIOMEDICAL SIGNAL COMPRESSION WITH OPTIMIZED WAVELETS

Mogens Nielsen[1], Nlandu Kamavuako[1], Michael Midtgaard Andersen[1], Marie-Françoise Lucas[2], Dario Farina[1]

[1]Center for Sensory-Motor Interaction (SMI), Department of Health Science and Technology, Aalborg University, Aalborg, Denmark (df@hst.aau.dk)
[2]IRCCyN, Ecole Centrale de Nantes, Nantes, France

ABSTRACT

In this work, we propose a novel scheme of signal compression based on signal-dependent wavelets. To adapt the mother wavelet to the signal for the purpose of compression, it is necessary to define a family of wavelets that depend on a set of parameters and a quality criterion for wavelet selection (i.e., wavelet parameter optimization). We propose the use of orthogonal wavelets parameterized by their scaling filter, with optimization criterion based on the minimization of signal distortion rate given the desired compression rate. For coding the wavelet coefficients we adopted the embedded zerotree wavelet coding algorithm. Results on electromyographic signals show that optimization significantly improves performance.

1. INTRODUCTION

Telemedicine applications are of growing interest since they provide easy access to diagnostic and assessment procedures [1]. The need to transmit large amount of data motivates the necessity of data compression without loosing the relevant information carried by the signals. Past research has focused on a number of compression schemes, especially in the fields of electrocardiogram and electroencephalogram [2][3][4]. Wavelet representations have been widely used and many algorithms based on the discret wavelet transform (DWT) have been proposed for signal compression. In all cases, the mother wavelet is selected from a catalogue or chosen by comparing the results of a few wavelets on a set of experimental signals [5][6][7]. Coifman and Wickerhauser [8] proposed an entropy-based algorithm for selecting among a library of functions (such as wavelet packets) an orthonormal basis relative to which a given signal has the lowest information cost (best basis), but the choice of the mother wavelet is fixed a priori. However, it is expected that the best wavelet depends on the specific features of the signal to be compressed and, thus, that a signal-based selection of the mother wavelet is necessary for optimal compression with respect to minimizing the reconstruction error. Moreover, it is often not possible to select a-priori the optimal wavelet since this depends on the signal features and on the coding scheme.

Thus, in this study we propose a signal-based optimization of the mother wavelet. To adapt the mother wavelet to the signal for the purpose of compression, we define 1) a family of wavelets that depend on a set of parameters and 2) a quality criterion for wavelet selection (i.e., wavelet parameter optimization). Concerning point 1), we focus on orthogonal wavelets defined in the multiresolution analysis (MRA) framework, and take directly the coefficients of the scaling filter (to be used in the Mallat's pyramidal algorithm) as the parameters. Concerning the criterion, a natural quality criterion is the distortion rate of the compressed signal given a target compression rate. For coding of the wavelet coefficients we will adopt the embedded zerotree wavelet (EZW) coding algorithm, which was originally proposed for coding two-dimensional signals [9]. However, the wavelet optimization can be applied to any coding scheme.

This paper is organized as follows : in section 2 we present the compression algorithm, with the wavelet parameters optimized with respect to the quality criterion. Results on electromyographic signals are shown in section 3 and discussed in section 4.

2. COMPRESSION ALGORITHM

The compression algorithm is based on the DWT of the signal followed by the EZW coding scheme. The DWT depends on the mother wavelet which is selected by wavelet parameterization [10] with the criterion of minimal distortion on the compressed signal given a desired compression rate.

2.1. Wavelet parameterization

In the MRA framework [11] the scaling function ϕ and its associated mother wavelet ψ are related to the filters h and g (used for computation of the DWT) by the two-scale recursive relations $\phi(t/2)=\sqrt{2}\sum h[n]\phi(t-n)$ and $\psi(t/2)=\sqrt{2}\sum g[n]\phi(t-n)$. For orthogonal wavelets, g

can be deduced from h from the relation $g[k]=(-1)^{1-k}h[1-k]$, thus h defines ψ. However, to generate an orthogonal MRA wavelet, h must satisfy some constraints. For a finite impulse response (FIR) filter of length L, there are $L/2+1$ sufficient conditions to ensure the existence and orthogonality of the scaling function and wavelets [12][13]. Thus $L/2-1$ degrees of freedom remain to design the filter h. The lattice parameterization described by Vaidyanathan [14] allows us to design h via unconstrained optimization. We denote θ the design parameter vector. For instance, if $L = 6$, we need a 2-component design vector, $\theta = [\alpha, \beta]$, and h is given by [15][16]:

$$i = 0,1 : h[i] = 4\sqrt{2}[(1 + (-1)^i \cos\alpha + \sin\alpha)(1 - (-1)^i \cos\beta - \sin\beta) + (-1)^i 2\sin\beta\cos\alpha]$$

$$i = 2,3 : h[i] = 2\sqrt{2}[(1 + \cos(\alpha - \beta) + (-1)^i \sin(\alpha - \beta)]$$

$$i = 5,6 : h[i] = 1/\sqrt{2} - h(i-4) - h(i-2)$$

2.2. Embedded zerotree wavelet coding

The EZW algorithm [9] is based on two main features. First, it exploits the framework of the DWT or any transform that yields a hierarchical subband decomposition, and establishes a connection between coefficients from different subbands. This property allows one to encode multiple coefficients simultaneously, which makes it an effective algorithm in DWT-based compression. Second, the encoding is based on bit prioritization, i.e., the coefficients are encoded in terms of importance. The embedded coding scheme places the most important bits in the beginning of the bit-stream, thus the encoding or decoding process can terminate at any time and allow a target bit-rate or distortion rate to be met exactly.

2.3. Quality criterion

In the context of compression a natural quality criterion is the distortion rate given a desired compression rate. Compression rate was defined in this study as:

$$CR(\%) = \frac{Os - Hs}{Os} \cdot 100, \qquad (1)$$

where Os is the original data size in bits and Hs is the Shannon entropy of the output of the coding algorithm [17]. Thus, it is assumed that an ideal lossless compression is applied to the output bit stream of the EZW coding.

The distortion rate was defined as (percent residual difference):

$$PRD(\%) = \sqrt{\frac{\sum_n (x_0[n] - x_r[n])^2}{\sum_n x_0[n]^2}} \cdot 100 \qquad (2)$$

where $x_0[n]$ is the original signal and $x_r[n]$ is the signal obtained after compression and decoding.

2.4. Overall algorithm

Figure 1 depicts the overall algorithm. The first step in the algorithm is the computation of the DWT of the input signal that depends on the parameter θ. Using the parameterization scheme, there are many DWT bases available, which represent the signal in different ways. The wavelet coefficients are then the input of the EZW block, which performs quantization, encoding and decoding operations on the coefficients. The encoding step stops when the target compression rate is met.

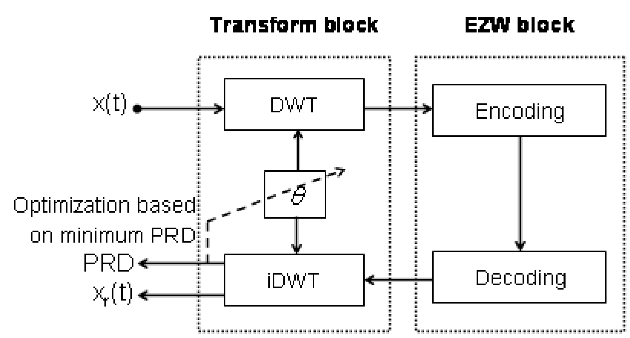

Figure 1 Compression algorithm diagram. $x(t)$ is the input to the compression algorithm. The DWT representation of $x(t)$ is passed as input to the EZW coding scheme. The encoding process continues until a predefined target bit-rate is met. The iDWT block carries out the inverse DWT on the decoded wavelet coefficients, and it returns a distortion metric PRD and the reconstructed signal $x_r(t)$. The distortion metric is compared among the set of parametrized wavelets and its minimum identifies the optimal wavelet. θ is the parameter vector which defines the wavelet.

In this paper, the optimization of θ is done by an exhaustive search on a grid (sampling of the parameters α, β and computation of the criterion on each node).

3. COMPRESSION OF EMG SIGNALS

3.1. Recording of surface EMG signals

Surface EMG signals were recorded from the upper trapezius muscle of 10 healthy male volunteers (age, mean ± SD, 25.6 ± 2.4 yr). The subjects were in an erect posture (adducted shoulder girdles), with both arms abducted at 90 degrees. Data were recorded with bipolar electrodes (Neuroline 720-01-k, Ølstykke, Denmark) placed 31 mm apart, 20 mm lateral with respect to the mid-point between the acromion and the seventh cervical vertebra. The signals were amplified 2000 times, bandpass filtered (2-500 Hz), digitized on 12 bits, and sampled at 1 kHz.

3.2. Results

For the set of signals analyzed, filter length L = 6 led to significantly better performance than filter length L = 4 (two-way ANOVA with factors compression ratio and filter length; $P < 0.05$), while no additional improvement was obtained with filter length 8. The step size for the two parameters in the optimization procedure was fixed to $\pi/7$, which resulted in PRD not significantly smaller than those obtained with smaller step sizes.

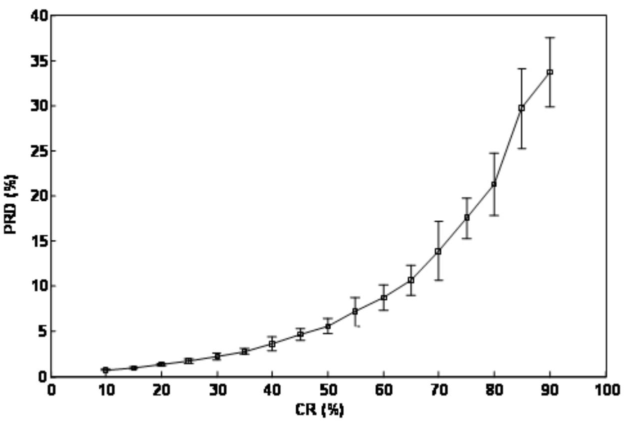

Figure 2 PRD vs. CR (mean ± SD, over all subjects) for entropy-based decomposition with optimal wavelet.

Figure 2 shows the CR/PRD plot over all subjects tested when the optimal wavelet is applied. The PRD was on average below 15% with CR up to 70%. An example of original signal and signal compressed with CR = 70% and 90% with optimal wavelet is reported in Figure 3. Note that the optimal wavelet also depends on the CR selected.

Figure 4 shows the PRD resulting from the optimal wavelet in comparison with three standard wavelets and with the wavelet resulting in the worst distortion rate among those tested, for CR 50% and 70%. A two-way ANOVA of PRD with factors the wavelet type (optimal, Daubechies, Coiflet, biorthogonal) and CR (10%-90%, step 10%) was significant for both factors ($P << 0.001$ for the wavelet type).

4. DISCUSSION

We have proposed a new compression algorithm based on signal representation on a wavelet basis with optimization of the mother wavelet. The algorithm can be applied to any signal since the basis function is adapted to the specific signal features and allows optimal representation of the signal. Representative results have been shown for a set of surface EMG signals.

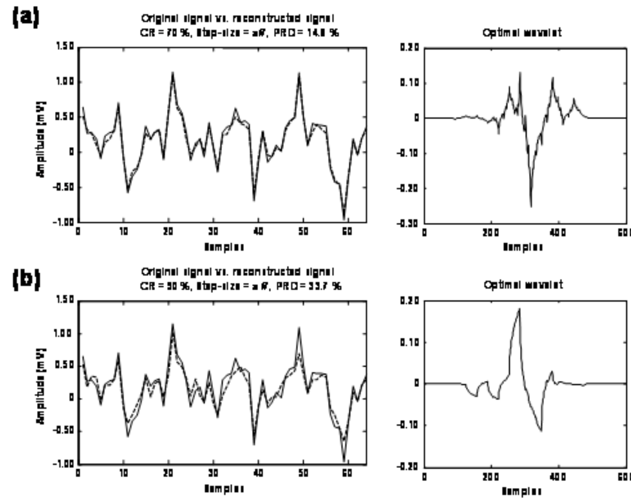

Figure 3 Example of an EMG signal (solid line) and its version after compression (dashed line) with optimal wavelet for CR = 70% (a) and CR = 90% (b). The optimal wavelet in the two cases is shown on the right. Note that the optimal wavelet depends on the CR for the same signal.

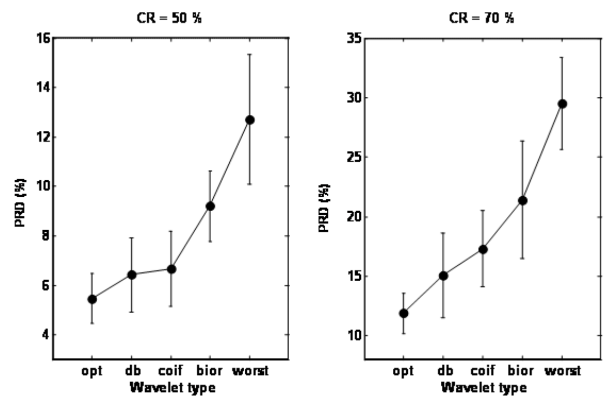

Figure 4 PRD (mean ± SD, over all subjects) corresponding to CR = 50% (a) and CR = 70% using three standard wavelets (db = Daubechies, Coif = Coiflet, bior = biorthogonal), the worst and the best (opt) wavelets.

The problem of optimizing the mother wavelet was not addressed in previous wavelet-based compression. One mother wavelet may be better than another for a specific signal or for the same type of signal collected on different subjects or in different experimental sessions. Moreover, the wavelet may also depend on the desired compression rate (Figure 4). In most cases, it is not possible to choose a-priori the best wavelet, which also depends on the encoding scheme. In order to optimize the wavelet, parameterization is necessary, as it was done in this study. It was shown that within the same type of signals (EMG), the selection of a single mother wavelet for all subjects leads to poorer results than in case of signal-based optimization (Figure 5).

5. REFERENCES

[1] Clarke LP, Qian W, Kallergi M, Venugopal P, Clark RA. Hybrid wavelet transform for image enhancement for computer-assisted diagnosis and telemedicine applications. In: Akay M (Ed.) Time frequency and wavelets in biomedical signal processing. IEEE Press, 1998.

[2] Istepanian RSH, Petrosian AA. Optimal zonal wavelet-based ECG data compression for a mobile telecardiology system. IEEE Trans Inf Technol Biomed 4: 200-211, 2000.

[3] Jalaleddine SMS, Hutchens CG, Strattan RD, Coberly WA. ECG data compression techniques – a unified approach. IEEE Trans Biomed Eng 37: 329-343, 1990.

[4] Yloestalo J. Data compression methods for EEG. Technol Health Care 7: 285-300, 1999.

[5] Norris JA, Englehart KB, Lovely DF. Myoelectric signal compression using zero-trees of wavelet coefficients. Med Eng Phys 25: 739-46, 2003.

[6] Rajoub BA. An efficient coding algorithm for the compression of ECG signals using the wavelet transform. IEEE Trans Biomed Eng 49: 355 – 362, 2002.

[7] Wellig P, Cheng Z, Semling M, Moschytz GS. Electromyogram data compression using single-tree and modified zero-tree wavelet encoding. In: Proc IEEE–EMBS 1303–6, 1998.

[8] Coifman R.R., and M.V. Wickerhauser. Entropy-based algorithms for best basis selection. IEEE Transactions on Information Theory, 38(2):713--718, March 1992.

[9] Shapiro JM. Embedded image coding using zerotrees of wavelet coefficients IEEE Trans Signal Proc 41: 3445 – 3462, 1993.

[10] A. Maitrot, M-F. Lucas, C. Doncarli, D. Farina, "Signal-Dependent Wavelets for Electromyogram Classification", Med. Biol. Eng. Comput., in press.

[11] Mallat S. A theory for multiresolution signal decomposition : the wavelet representation. IEEE Trans Pattern Anal 11: 674-693, 1989.

[12] Lawton W. Tight frames of compactly supported affine wavelets. J Mathematical Physics 31: 1898-1901, 1990.

[13] Lawton W. Necessary and sufficient conditions for constructing orthonormal wavelet base. J Mathematical Physics 32: 1440-1443, 1991.

[14] Vaidyanathan PP. Multirate Systems and Filter Banks. Wellesley-Cambridge Press, 1996.

[15] Burrus CS, Gopinath RA, Guo H. Introduction to wavelets and wavelet transforms. Prentice Hall, 53-66, 1997.

[16] Selesnick IW. Maple and the parameterization of orthogonal wavelet bases, 1997. Available Online: http://taco.poly.edu/selesi/theta2h/

[17] Proakis J. Digital Communications. McGraw Hill, 2001.