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A New Wavelet-Based Algorithm for Compression of Emg Signals

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Abstract—**Despite the growing interest in the transmission and storage of electromyographic signals for long periods of time, only a few studies dealt with the compression of these signals. In this article we propose a novel algorithm for EMG signal compression using the wavelet transform. For EMG signals acquired during isometric contractions, the proposed algorithm provided compression factors ranging from 50 to 90%, with an average PRD ranging from 1.4 to 7.5%. The proposed method uses a new scheme for normalizing the wavelet coefficients. The wavelet coefficients are quantized using dynamic bit allocation, which is carried out by a Kohonen Neural Network. After the quantization, these coefficients are encoded using an arithmetic encoder. The compression results using the proposed algorithm were compared to other algorithms based on the wavelet transform. The proposed algorithm had a better performance in compression ratio and fidelity of the reconstructed signal.**

I. Introduction

ELECTROMYOGRAPHIC (EMG) signals are a useful tool in the assessment of muscle behavior [1,2]. The storage and transmission of this signal is usually an issue (e.g., in telemedicine applications), as EMG signals are usually digitized with sampling rates ranging from 1 to 20 kHz and with a precision between 12 and 16 bits/sample [1].

Previous works have dealt with the compression of other kinds of biomedical signals, such as the electrocardiogram [3,4,5] and the electroencephalogram [6]. Few works addressed EMG signal compression.

Norris and Lovely [7] investigated the compression of EMG signals, using ADPCM (Adaptive Differential Pulse Code Modulation). Guerrero and Maihes [8] used different lossless compression methods, and compared the results with those of other methods, including methods based on orthogonal transforms. Such methods had a better performance regarding the compression rate and the signal to noise ratio. The compression of EMG signals using the Embedded Zero-Tree Wavelet has also been studied [9,10]. More recently, Berger *et al.* [11], proposed an algorithm for EMG signal compression using the wavelet transform, and a scheme for the dynamic allocation of the bits that represent the wavelet coefficients.

In this work, we propose a new algorithm for the EMG signal compression, based on the algorithm presented in [11]. In the proposed method, EMG signals are transformed to the wavelet domain, and the wavelet coefficients are normalized before the quantization stage. The quantization is performed by a dynamic bit allocation process, using a Kohonen neural network. The resulting coefficients are then quantized by an arithmetic encoder.

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II. Materials and Methods

A. Wavelet Transform Compression

The wavelet transform is a time-scale decomposition with basis functions that are translations and dilations of a prototype function called mother wavelet [12]. The basis functions are based on a scale function, in such a way that:

$$\varphi(\mathrm{t}) = \sum_{\mathrm{k}=-\infty}^{\infty} \mathrm{g(k)}\sqrt{2}\varphi(2\mathrm{t}-\mathrm{k}) \tag{1}$$

$$\psi(\mathrm{t}) = \sum_{\mathrm{k}=-\infty}^{\infty} \mathrm{h(k)}\sqrt{2}\varphi(2\mathrm{t}-\mathrm{k}), \text{for } \mathrm{k}=1,2,... \tag{2}$$

$$\psi_{\mathrm{j,k}}(\mathrm{t}) = 2^{\mathrm{j}/2}\psi(2^{\mathrm{j}}\mathrm{t}-\mathrm{k});\ \mathrm{j,k}=1,2,... \tag{3}$$

The coefficients g(k) are the coefficients of the scale function. The h(k) coefficients are the coefficients of the wavelet function, or the wavelet filter. With the appropriate choice for g(k) and h(k), any continuous function can be decomposed into a series expansion, according to the following equation:

$$x(t) = \sum_{k=-\infty}^{+\infty} c_{j_o}(k)\varphi_{j_o,k}(t) + \sum_{j=j_o}^{+\infty} d_j(k)\psi_{j,k}(t) \tag{4}$$

In this equation, the first summation yields the resolution function – j_o –, which is a low resolution approximation of x(t). In the second summation, for each increment of j, a higher resolution function is added to x(t), and fine detail is successively added. The set of coefficients represented by equation (4) is called the discrete wavelet transform (DWT).

The DWT coefficients, in the j-th scale, are related to the coefficients in the j+1-th scale, according to the following equations:

$$c_j(k) = \sum_{n=-\infty}^{\infty} g(n-2k)c_{j+1}$$
$$d_j(k) = \sum_{n=-\infty}^{\infty} h(n-2k)c_{j+1}, \quad (5)$$

where $c_j(k)$ are the approximation coefficients, and $d_j(k)$ are the detail coefficients. The above equations provide a recursive way for calculating the DWT coefficients. In practice, it is assumed that a discrete signal in its original resolution is equivalent to the approximation coefficients.

Thus, if the set of filters h(k) and g(k) are chosen in such a way that they have a finite number of non-zero coefficients, that is, they are FIR filters, the DWT can be calculated by the filter bank shown in Figure 1, up to the j_o–th scale, where $\hat{h}(k)=h(-k)$ and $\hat{g}(k)=g(-k)$. The set of filters that are used in this work were the biorthogonal 9/7, that have been shown to be very effective in the compression of ECG signals [4,5].

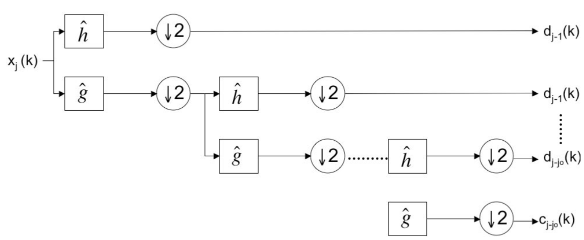

Fig. 1. Wavelet Decomposition Algorithm.

B. *Wavelet Coefficient Normalization*

In this work we propose a new scheme for the normalization of the wavelet coefficients. In the proposed approach, the coefficients are multiplied by two scale factors, calculated by equations 6 and 7:

$$\varepsilon_k = \left(\frac{1}{\sqrt{2}}\right)^{J_k} \quad (6)$$

where k is the index of the transformed coefficient and J_k is the decomposition scale to which the k coefficient belongs, and

$$\lambda_i = \frac{2^Q}{\max\{|X_i[k]|\}} \quad (7)$$

where i is the index of the block that is being processed, Q is the quality factor and $X_i[k]$ are the transformed coefficients of the i-th element.

The scale factors of the ε_k-th scale need not be transmitted to the decoder, since the values of ε_k can be calculated by the decoder once the resolution of the wavelet transform is chosen. The goal of this normalization stage is to compensate the gains of the analysis filters of the wavelet decomposition process. On the other hand, the normalization factors – λ_i – need to be transmitted as overhead information to the decoder, as they depend on the input signal, and not only on the resolution that was chosen for the wavelet transform.

The normalization process, along with the DWT and the quantization, leads to the appearance of many null coefficients in the quantization stage. This combination leads to a thresholding effect that adapts itself locally to the statistics of the signal, and yields a better signal-to-noise ratio than traditional transform-based coders, which employ a fixed threshold for each block. Another advantage of this normalization approach is that it provides a method for controlling the quality of the reconstructed signal. In this method, the number of coefficients that are null, or that can be quantized with few bits, is proportional to the specified quality factor. The normalization factor λ_i is proportional to the value of 2^Q in equation 6. Therefore, a small 2^Q value leads to a small number of bits being allocated for the transformed coefficients.

C. *Encoding of Wavelet Coefficients*

The encoding algorithm proposed in this work can be represented by the block diagram in Figure 2. The input signal is divided in blocks of 2048 samples, and each block is transformed to the wavelet domain. The wavelet coefficients are normalized as described in the previous section.

After normalization, each block of 2048 transformed coefficients is divided in 16 sub-bands. For each sub-band, the amount of bits that the transformed coefficients need is calculated, and this calculation leads to a 16-sample temporary bit allocation vector.

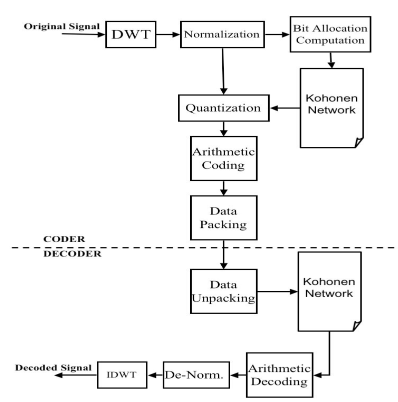

Fig. 2. Block-diagram of the proposed encoder and decoder.

The bit allocation vector is determined with the aid of a Kohonen layer as illustrated in Figure 3. Each block of 2048 coefficients is divided into 16 sub-bands of 128 spectral lines. The ideal bit allocation for each sub-band is calculated. A vector with the ideal bit allocation scheme for all sub-bands in the signal segment is then built. This temporary bit allocation vector is applied to a Kohonen layer neural network. After processing by the Kohonen layer, a new approximated vector is chosen, which yields the final bit allocation vector.

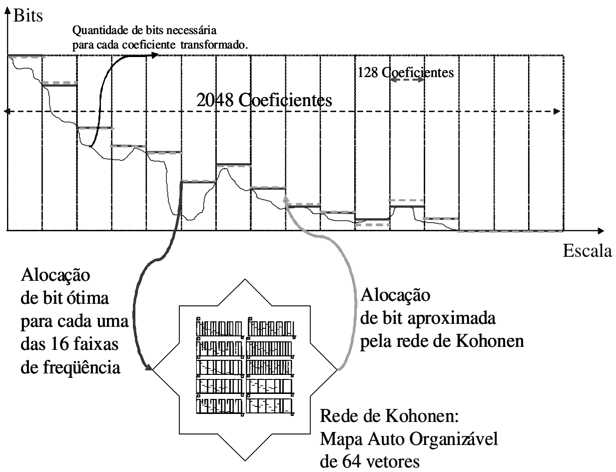

Fig. 3. - Illustration of the bit allocation algorithm.

The Kohonen network that was used has a rectangular, 8x8 neurons topology, which represents a dictionary with 64 vectors. The Kohonen network was trained with the Winner Takes Most (WTM) algorithm, assuming a Gaussian neighborhood function. It is important to notice that Kohonen layer training is done completely off-line and a real-time implementations of the proposed algorithm, although possible, would depend on the latency of the encoder hardware architecture. Six bits per block are needed for transmitting the index of the bit allocation vector to the decoder. Once this vector is determined, the transformed block is quantized. More details on the bit allocation and the quantization of the transformed coefficients are presented in [11]. The blocks with the quantized wavelet coefficients are grouped into a single sequence, which is encoded using arithmetic coding [13]. In order to achieve optimal entropy coding, the probability distribution of the alphabet symbols should be known a priori. In practice, this probability distribution is not known, and should be "learned" by the encoder and decoder, based on past observations of the encoding/decoding process. In this sense, a source with a reduced-size alphabet provides higher compression gains. The normalization process described in the previous section favors the use of the arithmetic coder, as it provides automatic control for the gains of the wavelet coefficients, which reduces the number of symbols of the input alphabet.

III. Results and Discussions

The compression algorithms presented in the last section was tested with EMG signals that were collected from the *biceps brachii* in 14 subjects during isometric contractions at 60% of the maximum voluntary contraction. These signals were sampled at 2 kHz, and quantized using a 12-bits analog to digital converter. The duration of each signal ranged from 3 to 6 minutes.

The performance of the signal compression algorithm was measured using two criteria: the compression factor (CF) and the percentage root mean difference (PRD). These two criteria are currently the most commonly used criteria for assessing the quality of EMG signal compression. The compression factor is defined as:

$$CF = \frac{O_S - C_S}{O_S} \times 100\,\% \tag{8}$$

where O_S is the number of bits that is needed to store the original data, and C_S is the number of bits needed for storing the compressed data.

The percentage root mean difference is defined as:

$$PRD = \sqrt{\frac{\sum_{n=0}^{N-1} \left(x[n] - \hat{x}[n]\right)^2}{\sum_{n=0}^{N-1} x^2[n]}} \times 100\,\% \tag{9}$$

where $x[n]$ is the original signal, $\tilde{x}[n]$ is the reconstructed signal and N is the size of the signal segment.

Several tests with the proposed algorithm were carried out for different values of quality factors Q. The PRD was measured such that the results of the CF ranged from 50 to 100%. Figure 4 shows the results of CF versus PRD for all EMF signals tested, as well as the mean result. As the quality factor Q decreases, the compression factor CF increases. As a result of the increase in CF, the PRD remains almost unchanged up to the compression level of 85%. After this point, any small increase in the compression factor leads to a great deterioration in the reconstructed signal. This has already been observed in [11], where the same bit allocation scheme for the wavelet coefficient was used. Note that, using the proposed algorithm, it was possible to encode the EMG signals with a CF ranging from 50 to 90%, and PRD ranging from 1.4 to 7.5%, while, in [11], the CF ranged from 50 to 85%, and the PRD ranged from 2.4 to 7%. The comparison between these two results is accurate, as the same set of signals was used.

At this point it is not possible to compare, in an accurate and reliable way, the results of the proposed algorithm with the results presented in [9], as in that work the EMG were not measured at the skin surface, and were sampled at 10 kHz and quantized with 12 bits. These signals are very different from the signals used in this work, and a direct comparison with the proposed algorithm would not be possible.

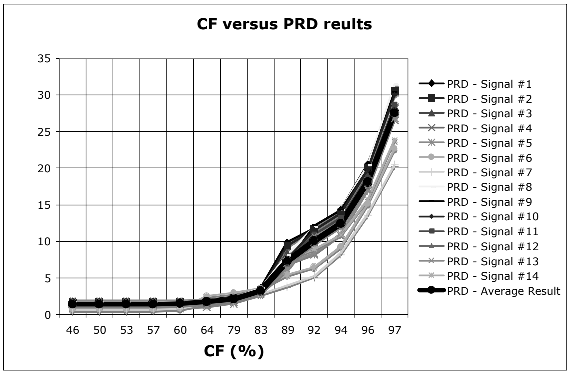

Fig. 4. Compression rates for the proposed algorithm

The algorithm proposed by Norris et al. [10] was tested with EMG signals measured during isometric and isotonic contractions. The isometric EMG signals were measured from the *biceps brachii* muscle, sampled at 2 kHz, and quantized with 12 bits. Thus, the signals are reasonably equivalent to the ones used in this work. In Figure 5, we compare the proposed algorithm with the Norris algorithm [10], and also with the algorithm by Berger et al. [11]. In the figure, it is clear that the algorithm proposed in this work had a better performance. However, It is important to highlight that the differences in performance between Norris's work and the proposed method may just reflect the fact that the sets of data used for the two methods may be have different characteristics. Although at a first glance the signals are similar to the ones used in the present work, details such as interelectrode distance and %MVC were not reported in Norris' work, and it is possible that the signals used in that work were different from the signals used in this one.

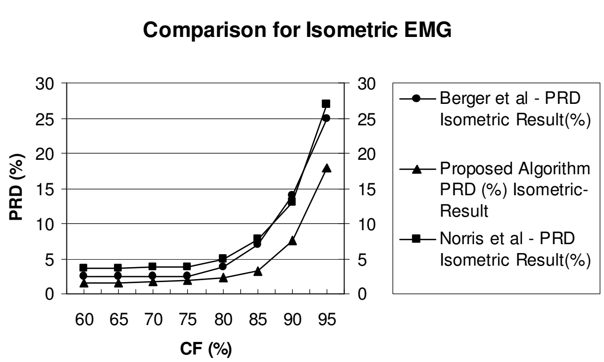

Fig. 5. Comparison between the proposed algorithms, and previous methods [10,11]. The method proposed in this article had a better performance.

IV. Conclusion

In this article, we proposed a new algorithm for the compression of surface EMG signals. Each block of the EMG signal is transformed using the DWT, normalized, and quantized using a dynamic bit allocation scheme based on a Kohonen neural network. The set of quantized coefficients is then encoded by an arithmetic coder. The compression of the EMG signals was evaluated with a set of 14 EMG signals measured during isometric compressions. The results showed that the compression factors ranged from 50 to 90%, and the PRD ranged from 1.4 to 7.5%. The performance of the proposed algorithm was better than that of existing algorithms that use the discrete wavelet transform.

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