

Compression of the EMG Signals by Walsh-Hadamard Transform Associated with the Predictive Coding DPCM

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Abstract: The EMG signals are vectors of several informations relative to the physiological and pathological state of muscles. The storing of these signals causes problems of storage space and bandwidth, a solution to this problem is compression. In this research, we compress the EMG signals by an algorithm based on the Walsh-Hadamard Transform (WHT). Then, we compress the same data by the Differential Pulse Code Modulation (DPCM) method. The method which we propose superposes the DPCM and the WHT. An evaluation of these three algorithms (WHT, DPCM and their superposition) is made. The performances of these methods are given by the measures of SNR, MFD, MSE, PRD and the CR. The originality of this algorithm which combines the decomposition by WHT and a method of linear prediction (DPCM), lies in the improvement of the compression ratio and the simplicity of implementation.

Key words: WHT, DPCM, compression, EMG, MSE, PRD

INTRODUCTION

The electromyographic signals (EMG) contains several types of information. These informations are important in the diagnosis, the prevention and the study of certain myopathies (Miller and Henry, 2009; Im *et al.*, 2010). In the manipulation of these signals, the information can either be stored or forwarded. The storage and the transmission cause, respectively, the problems of storage space and the bandwidth. So, the compression becomes necessary. The purpose of the compression is to reduce the size of the data. The compression of the data was always the field of several studies. Some of these studies aim at the improvement of the existing algorithms and the others are directed to the development of new algorithms and the compression formats. The compression of these data can be obtained from two ways according to, the main objectives. One consists in a projection of data on bases of orthogonal functions: case of lossy compression. While, the other one is a direct method because it codes the data in the same space as the source, this compression is lossless compression (Chowdhury and Khatun, 2012; SahuLal *et al.*, 2016).

Compression algorithms based on the Discrete Cosine Transform (DCT), the Karhunen-Loeve Transform (KLT), the Discrete Wavelet Transform (DWT) and hybrid algorithms were successfully applied to electrophysiological signals in general and the EMG

signals in particular. By Kuklinski (1983), developed a compression algorithm based on Fast Walsh Transform (FWT). In this algorithm, he implements a compression system of ECG data in real-time with microprocessors. This algorithm gives interesting results but, results do not concern the EMG signals moreover, only single transform is apply. By Yang *et al.* (2013) used Fast Walsh-Hadamard Transform (FWHT) to improve substantially the performances of the DWT. For that purpose, they divided the image into very small blocks of equal size and the FWHT was used for the extraction of the characteristics of each block. The duplicated regions are detected by sorting out lexicographically all the characteristics of the blocks of image (Yang *et al.*, 2013). By Sujithra *et al.* (2013) proposed a compression method of the hyperspectral images based on superimposing the DWT and the Discrete Walsh-Hadamard Transform (DWHT). In their algorithm, the DWT eliminates the spatial and spectral redundancy in the hyperspectral domain and the WHT bleaches the signal in the low-frequency sub-band (sub-strip). By Colince *et al.* (2014), developed an algorithm of EMG compression constituted by Differential Pulse Code Modulation (DPCM) algorithm followed by a transformation of the 1D EMG signal in 2D EMG signal. The 2D signal undergoes successively two discrete transformations: the DCT and the DWT. This research gave interesting results. However, the compression algorithm which combines the

Walsh-Hadamard transform and the coding by the DPCM method, in- spite of its potentials was never tested on the EMG signals or on any other signal. This study is made up of three parts: state of the art, methodology, analysis and the interpretation of the results.

State of the art

Compression generalities: One of the characteristics common to most of the images, is the correlation between the nearby pixels. The compression exploits the capacities of certain mathematical applications to delete the spatial or temporal redundancy and the non-relevant information for the receivers: the human sensors, for example, Daubechies (1992).

The data compression can be without or with loss (Shannon and Wiener, 1949; Jain, 1989). In the lossless algorithm of compression, after decompression, the reconstructed signal is identical to the original signal. This type of compression does not give high compression ratios and thus cannot be used in complex cases as that of the compression of the EMG signals. The techniques of lossy compression are used when we can sacrifice a number of not essential details in the signal. This type of compression gives high compression ratios. A lot of researchs is done to satisfy the needs for the compression. These researches aim mainly at the increase of the compression ratios, the improvement of the quality of the reconstructed signal and the reduction of the complexity of the existing algorithms of compression (Eloundou *et al.*, 2005; Uyar and Ider, 2001; Oyobe-Okassa *et al.*, 2016).

In the literature, we find several works based on orthogonal transformations realized for the compression of the EMG signals. Most of them used the DWT and the DCT (Feig and Winograd, 1992; Oyobe-Okassa *et al.*, 2016). The orthogonal transformations methods were recognized very effective to uncorrelate the data. By returning the signal in the frequency domain, the DCT for exemple allows to reduce the frequency redundancy. Furthermore, if we add a thresholding we are certain to reduce significantly the size of the information to store (Aharon *et al.*, 2006; Starck *et al.*, 2010). The general compression/ decompression scheme with the orthogonal transformations is presented in Fig. 1.

Figure 1 presents the general procedure of lossy compression/decompression. The original signal is decomposed by an orthogonal transformation. The effective orthogonal transformations are reversible, having a good parsimony of representation, having an algorithm of decomposition and a high bleaching power of data (Daubechies, 1992). This decomposition allows to

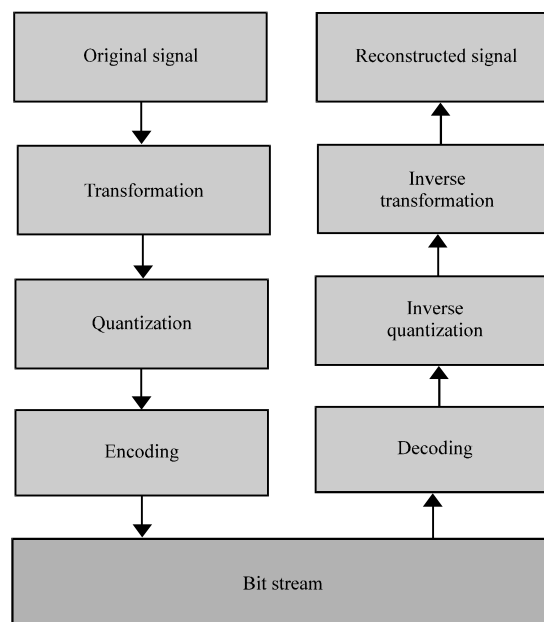


Fig. 1: Compression/decompression scheme using space transformation

uncorrelate the data. The obtained coefficients are quantized to limit the number of bits to be transmitted or stored. The decompression follows this algorithm but on the reverse scheme.

Evaluation parameters: The compression ratio is an important parameter in the quantitative evaluation of a compression algorithm. It is defined by Nelson (1993):

$$CR = \left(1 - \left(\frac{\text{size of compressed file}}{\text{size of original file}} \right) \right) \quad (1)$$

It is the main criterion of evaluation of a compression algorithm. But when it is the evaluation of a lossy compression scheme, it is necessary to associate this quantitative parameter with qualitative. The quality parameters allow to control the quality of the reconstructed signals and to compare the various compression approaches. The most used quality measure is the Mean Square Error (MSE) and it is defined by:

$$MSE = \frac{1}{N} \sum_{n=1}^N (s_0(n) - \hat{s}(n))^2 \quad (2)$$

Where:

- $s_0(n)$ = The original signal
- $\hat{s}(n)$ = The reconstructed signal
- N = The No. of signal samples

The most recommended measure is the Signal to Noise Ratio (SNR):

$$SNR = 10 \log \left(\frac{\sigma_x^2}{\sigma_e^2} \right) \quad (3)$$

Where:

σ_x^2 = The power of the original signal
 σ_e^2 = The power of reconstruction error

Berger *et al.* (2007) and Tisserand *et al.* (2008) presented two other criteria of evaluation of the quality of the reconstructed signal: the Mean Frequency Distortion (MFD) and the Percent Root mean square Difference (PRD). They are respectively defined by:

$$MFD = \left(\frac{|F_{orig} - F_{recons}|}{\max(F_{orig}, F_{recons})} \right)^2 \quad (4)$$

In Eq. 4, Forig and Frecons represent the average frequency calculated respectively on the original signal and on the reconstructed signal:

$$PRD = \sqrt{\frac{\sum_{n=0}^{N-1} (s(n) - \hat{s}(n))^2}{\sum_{n=0}^{N-1} (s(n) - \mu)^2}} \cdot 100\% \quad (5)$$

Where:

$s(n)$ = The original signal
 $\hat{s}(n)$ = The reconstructed signal
 N = The No. of the original signal samples
 μ = The baseline value of the analog-to-digital conversion used for the acquisition of the data $s(n)$ ($\mu = 0$ for the test EMG signals)

MATERIALS AND METHODS

Compression/decompression scheme: The compression/decompression scheme implemented in our algorithm is given in Fig. 2. The constituent elements are described in the lines which follow.

The DPCM step: The coding by Differential Pulse Code Modulation (DPCM) is a particular case of predictive coding. It extracts the unpredictable components of the original signal. For that purpose, the DPCM encoder contains a digital filter which predicts the signal sample (n) from the previous samples of $s(n)$. The only information transmitted is the difference $e(n) = s(n) - \hat{s}(n)$. The decoder reconstitutes the original signal by using the same predictive filter (Colince *et al.*, 2014). The schematic diagram of this algorithm is presented in Fig. 3. Other signals which we find on the diagram are the quantized

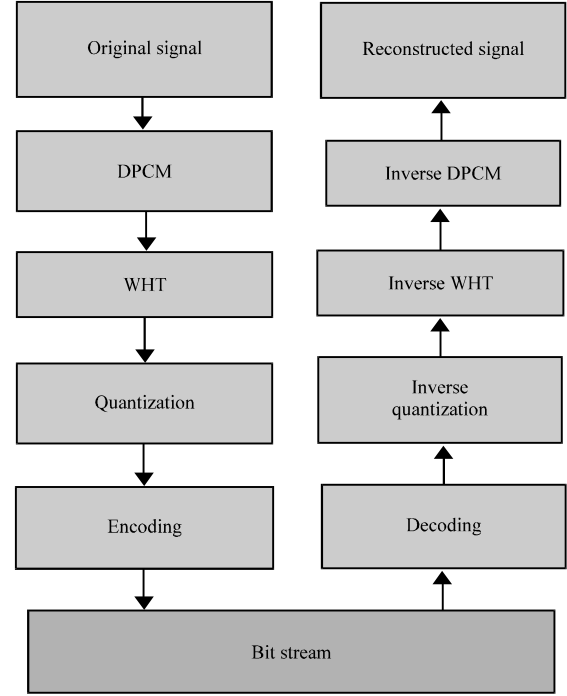


Fig. 2: Proposed compression/decompression algorithm

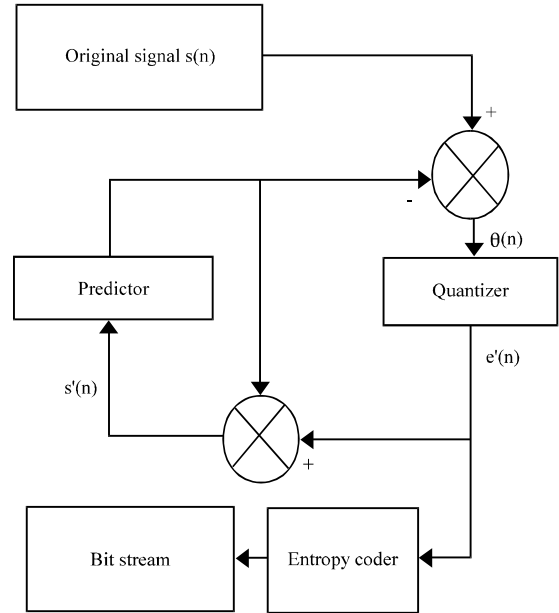


Fig. 3: DPCM method

prediction error $\hat{e}(n)$ and the local values of the decoded signal $\hat{s}(n)$. The advantage of this differential modulation is as greater as there is not high variation from one sample to the next. Equation 6 and 7 summarize the functioning of the coding method:

$$\text{Prediction error } e(n) = s(n) - \hat{s}(n) \quad (6)$$

$$\text{Re constructed signal } \hat{s}(n) = \hat{e}(n) + \hat{s}(n) \quad (7)$$

Where:

$\hat{s}(n)$ = The local signal of decoded signal

$s(n)$ = The original signal

The linear prediction is described by Eq. 8:

$$\hat{s}(n) = \sum_{i=1}^k h_i (s(n-1)) \quad (8)$$

with, $h = (h_1, h_2, \dots, h_k)^t$.

Walsh-Hadamard Transform (WHT) step: The Walsh-Hadamard transform is a non-optimal and orthogonal transformation. It decomposes a signal $s(t)$ to a set of orthogonal and rectangular functions called Walsh functions. The family of Walsh functions $W_n(t)$ allows to approach any signal with finite energy on an interval $(0; T)$. They form a complete set. Which allows to reach any wished precision by adapting the number N elements of the development. These functions take only the values 1 or -1 by changing n times the sign in open interval $(0; T)$. The WHT possesses a fast algorithm of decomposition with a computation cost $O(n \log n)$ (Beer, 1981; Beauchamp, 1984). The analytical determination of these functions obeys the relation (Eq. 9):

$$W_n(t) = \prod_{j=0}^{r-1} \text{sign} \left\{ \cos \left(n_j 2^j \pi \frac{t}{T} \right) \right\} \quad (9)$$

Where:

r = The smallest power of 2 superior to n

n_j = The state of j^{eme} bit of binary code of n

$$n = \sum_{j=0}^{r-1} n_j 2^j \quad (10)$$

The Walsh-Hadamard transform is the simplest transformation to be implemented. It makes a linear operation and involutive. Furthermore, it is orthogonal: what allows its use in compression algorithms. Recursively, we define a first transformation 1×1 via a matrix H_0 which is the matrix identity with a single element 1. We define then H_m for $m > 0$ thanks to the relation (Eq. 11):

$$H_m = \frac{1}{\sqrt{2}} \begin{pmatrix} H_{m-1} & H_{m-1} \\ H_{m-1} & -H_{m-1} \end{pmatrix} \quad (11)$$

The decomposition/reorganization by WHT for a signal $s(t)$ of length N are respectively, defined by Eq. 12 and 13:

$$a_n = \frac{1}{N} \sum_{i=0}^{N-1} s_i \text{WAL}(n,i), \quad n = 1, 2, \dots, N-1 \quad (12)$$

$$s_i = \sum_{n=0}^{N-1} a_n \text{WAL}(n,i), \quad i = 1, 2, \dots, N-1 \quad (13)$$

The coefficients of the WHT obtained are coded according to the coder of Huffman.

RESULTS AND DISCUSSION

Analysis and interpretation of the results: The method presented in this study was implemented on an actual EMG signal. It is 8192 points of the EMG taken from a muscle and baptized Kheir1 from the initials of the name of the person on whom these recordings were made. This signal is amplified with a gain of 2000, sampled with the frequency of 2048 Hz using 12 bits to code the data in the acquisition.

In this research, we compressed/decompressed the signals EMG by the method DPCM by the WHT and by the superimposing of the DPCM and WHT. Both types of possible alignments of the compression method by superimposing are tested (DPCM-WHT and WHT-DPCM). So, we observed the relation between the step of quantization and the compression ratio on one hand and on the other hand between the quantization step and the reconstruction error of the signals. The results of these three methods of compression/decompression are shown in Table 1 and 2 (Fig. 4 and 5).

The results presented in Table 1, the differences of qualitative and quantitative compression parameters of the reconstructed signals. Three methods give the same value of the distortion of the mean frequency except for the variant WHT-DPCM where it is 39.43 % and not 0.76%. This value of MFD indicates that three methods are stable on the frequency plan provided that the order of the transformations in the third algorithm is well chosen. The compression ratio makes some difference

Table 1: Evaluation of three algorithms

Algorithm	MSE	SNR	PRD	MFD (%)	CR (%)
DPCM	3.12E-12	41.97	0.79	0.76	48.89
WHT	2.1E-11	33.00	2.00	0.76	60.70
DPCM-WHT	2.29E-12	43.60	0.67	0.76	71.00
WHT-DPCM	3.06E-10	22.14	7.80	39.43	58.65

Table 2: Evolution of the parameters of DPCM-WHT algorithm according to the quantization step

Quantization step	MSE	SNR	MFD (%)	PRD	CR (%)	Reconstruction error
E-7	3.40 E-14	61.69	0.70	0.082	52.24	-1.84 E-07
E-6	2.29 E-12	43.60	0.76	0.670	71.00	1.51 E-06
E-5	9.70 E-09	7.14	51.16	43.920	90.88	9.85 E-05
E-4	4.77 E-08	0.22	72.86	97.420	91.66	2.18 E-04
E-3	-	-	-	-	-	-
E-2	-	-	-	-	-	-
E-1	-	-	-	-	-	-

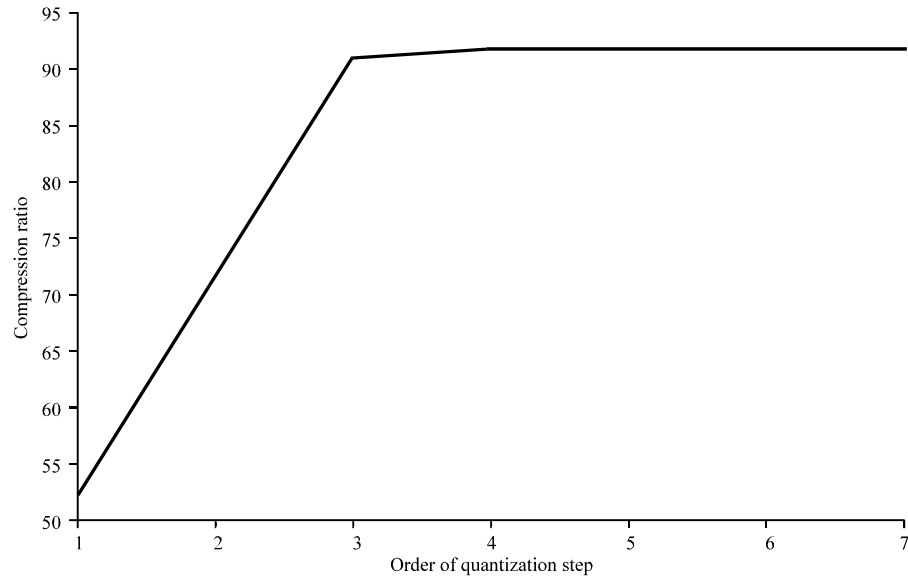


Fig. 4: Evolution of compression ratio as function of quantization step

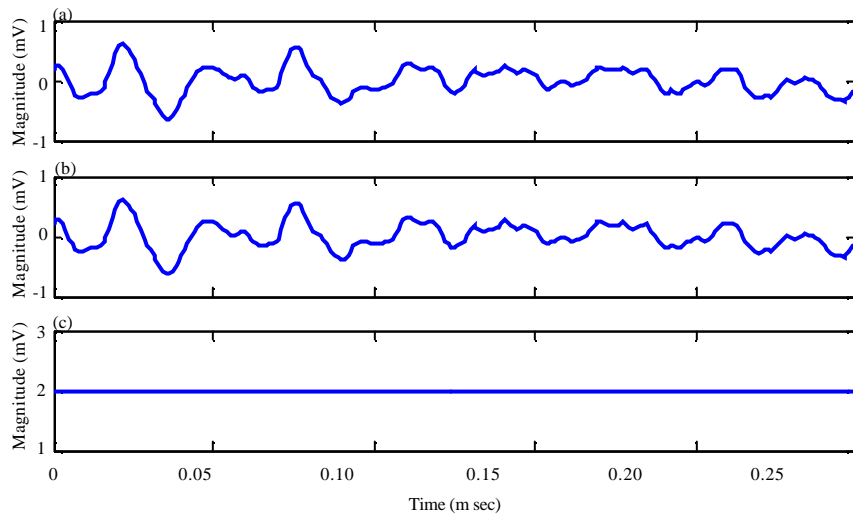


Fig. 5: a-c) Comparative representation of the original and reconstructed signals

between the three methods. According to, the results presented by Table 1, the use of the DPCM to code the samples of the original signal and the decomposition by WHT of these coded samples brought a significant

improvement at the same time from the point of view of the qualitative parameters (MSE, SNR and PRD) that of the quantitative plan (CR). This improvement is due on one hand to the coding DPCM which reduced

significantly the size of the signal samples. And on the other hand by the WHT which improved the compaction and the bleaching of these new samples. The choice of the compression ratio is commanded by the quality of the reconstructed signal required by the application. Table 2 is a mark for this choice.

Table 2 presents the evolution of the parameters of compression of the algorithm proposed according to, the quantization step. According to this table, a fine quantization step gives a reconstructed signal almost completed to the detriment of the compression ratio. However, the unrefined quantization step improves the compression ratio while destroying the signal quality. In this algorithm the parameters of compression evolve according to the quantization step then tend asymptotically towards a finished limit as presented by Fig. 4.

Figure 4 shows how the compression ratio evolves according to, the quantization step. The observed asymptotic trend is understandable by the fact that from the step of quantization E-4, the coefficients of WHT become all zeros. Their reconstruction gives values which are all zeros. So, from these zeros, the algorithm DPCM realizes the prediction of the EMG signal according to, Eq. 7. The results of the compression/decompression of the proposed algorithm are represented in Fig. 5.

The result of the compression/decompression by this method is assessed by the compression parameters which are the following ones: SNR = 43.60 dB, MSE = 2.29E-12, MDF = 0.76 % and CR=71 %. In spite of the good quality of the reconstructed signal obtained by the methods object of comparison, their compression ratios remain lower than those obtained by the proposed method. The reconstruction error of the proposed method is a constant and very close to zero (1.5154E-6 microV), this confirms the objective character of the good quality of the reconstructed data.

CONCLUSION

In this study, we presented a new method of compression/decompression which is better compared to the compression/decompression method of the DPCM or the algorithm of the WHT taken alone. It emerges from Table 1 that qualitatively and quantitatively, the superimposing of the DPCM and the WHT gives better results. The WHT method gives the best compression ratios compared to the DPCM method, to the detriment of the signal quality. The distortion of the mean frequency is the same for the three methods except for the case of the superimposing of methods in the order WHT-DPCM. The obtained results are encouraging with regard to the

objective and subjective criteria (SNR, MSE, MFD, CR and visual observation). This purposed method has a moderate load of calculation because it uses two linear transformations. Its compression ratios are high if we take into account the fact that the reconstruction is almost perfect.

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