Compression of EMG Signals by Super imposing Methods: Case of WPT and DCT

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***Abstract* - The objective of this work is to apply on the electromyographic signals (EMG) a new compression approach. The originality of this algorithm, that improves the compression ratio of the EMG signals, compared to Modified Algorithm of Decomposition (MAD),is the association of the Discrete Wavelet Packet Transform (DWPT) with the Discrete Cosine Transform (DCT). Indeed, the compression algorithms are intended principally to increase the compression ratio while maintaining the reconstructed signalquality. The results obtained by this method are interesting with regard to evaluation criteria of compression.**

Key words - Modified Algorithm of Decomposition, DWPT, DCT, EMG

I. INTRODUCTION

A general observation around us shows that the digital world occupies a special place in our immediate environment. There are many reasons for this occupation (facilitation of information interchange, entertainment and others). With digitization and the internet, data are shared. It is undeniable that the speed of exchanges allowed by scanning is areal progress. Another advantage of digital is its robustness. Now data can be copied many times without losing quality. The richness of information content changes every day. Certainly one observes every year an increase of the storage capacity of our hard disks, the new miniaturization of electronic components or the presence of the optical fibers of broader bandwidth; in brief our inventiveness exceeds the capacity of our current material supports. It is at this moment that the compression intervenes, to reduce the size of the data to store or to transmit.

Indeed the EMG signals support multiple types of information on the physiology and pathology of the muscles [1], [2]. This useful information must be exchanged or stored. The storage requires much space and transmission takes a long time. Therefore, it is necessary to compress thisinformation. In the literature, two types of compression are found: lossless and lossy compression. Despite the best qualities of reconstruction by lossless compression, lossy compression is chosen here, due to its high compression ratio. This compression method is based on processing data in another space called the transform space.

The rest of this article is organized as follows.In the section II is presented a state of the art of the compression methods; the third section is devoted to the methodology and the last one is reserved for the analysis and interpretation of the results.

II. STATE OF THE ART

Several works were presented for data compression. These works have given results with various successes. In this section is presented what was done in the field. The most used quality assessment methods in compression are also presented.

A. Compression Methods

There are several compression methods. One distinguishes the lossless and the lossy methods. The lossless methodsare applied on texts, archives, executable files…The most usual are: Differential Pulse Code Modulation (DPCM), Run Length Encoding (RLE), arithmetical coding, entropic encoding… The most usual lossy methods are included in transformations methods (Karhunen-Loeve Transform(KLT), Fourier Transform and its variants like DCT, Wavelet Transform and its variants like WPT…), prediction methods (DPCM), fractal methods and under sampling methods.Lossy methods are applied on images, sounds, video… and include usually a lossless coding step. The compression methods using the oriented transforms have been applied successfully on electrophysiological signals [3], [4], [5]. Most of these methods gave rise to algorithms of compression bound to the specific characteristics of the processed signal thus, not applicable in a general way in the compression. This justifies the existence of many compression algorithms [6], [7]. Due to the nature of the signal, these transformations must be able to better localization in both time and frequency. For an optimal efficiency of the transform, it must be orthogonal and computed by a fast algorithm [8]. The overall compression algorithm using a transformed space to encode data is shown in Fig.1.

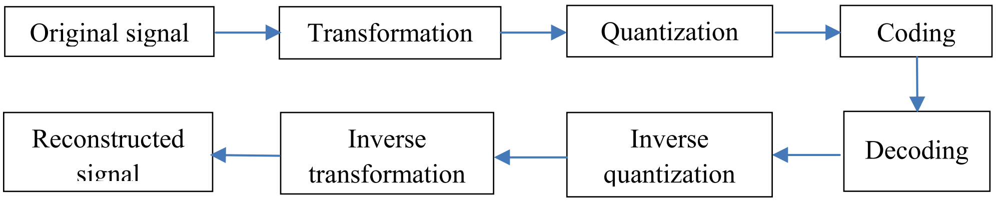

Fig. 1. General compression scheme

Fig. 1 shows the steps used to compress a signal. The original signal undergoes a transformation through a mathematical operator. The coefficients obtained are quantized to substantially reduce the number of bits to be encoded. For reconstruction, the signal is successfully processed by a decoder, an inverse quantization and an inverse transformation.

The researches in the field are primarily to increase the compression ratio, to improve the quality of the reconstructed signal, to reduce the complexity of existing compression algorithms and to develop new algorithms [9], [10]. In the case of electrophysiological signals in general, there are many publications. However, there is very few published works concerning the electromyographic signals. For compression of EMG, some methods such as those based on orthogonal transformations were used [11],[12]. The methods known as orthogonal transforms are recognized very effective todecorrelate data. This outstanding efficiency is mainly due to two properties that are the parsimony of representation and data whitening [13], [14]. In the literature, some algorithms based on the transformations are proposed and the most used in compression are presented.

The KLT is intended to transform a data table to give a better interpretation. The idea of the transformation is to achieve a change of basis for new area where the information on each axis is distributed optimally. The first important property of this transformation is the total decorrelation of the new data. Thus, the KLT has been used in some compression applications [15], [16]. In KL space, all the energy is contained in the sum of the eigenvalues. Despite the large capacity of KLTto compact the signal energy, it is rarely used in practice. This lack of interest for the KLT useis partly due to the fact that on the one hand, the transform matrix for a block of the image for example, is derived from the covariance matrix, which must be calculated for each block (this makes them dependent data at transformation and involves non-trivial calculations). And on the other hand there is to date no fast algorithm for its implementation.

The methods derived from the Fourier transform were used for compression applications with varying successes. However, Priyanka et al.[17], have shown that Discrete Cosine Transform is better than the Discrete Fourier Transform (DFT) and Discrete Sine Transform (DST). The DCT is one of the transformations that have a good concentration of signal energy. From the point of view of the decorrelation capacity, DCT is a better approximation of KLT. However, DCT has a great advantage over the KLT from having a fast calculation algorithm. Thus it was used in the JPEG algorithm [18].

DWT is one of a most famous transformation method for data compression. Usage of DWT method in the form of Embedded Zero-tree Wavelet (EZW)is efficient. TheEZW has a very interesting property. It encodes exact information by order of importance in the signal. Indeed, the coefficients are coded from most significant to least significant. The advantage is obvious: to get lossless compression, all the coefficients are coded; and for lossy compression, simply thresholding the coefficients obtained taking into account the eligible losses[19].

MAD, proposed in [20] is a compression algorithm that gives interesting results. It is based on the wavelet decomposition of order N of detail coefficients. The data obtained from this transformation are regularly decimated at the end of each iteration. The coefficients of decimated approximations are stored once and at the first iteration. Approximations obtained after decomposition of the details are of low energy and therefore not necessary for the reconstruction (the principle of thresholding). Compression of the EMG signal by MAD allows both to achieve a nearly lossless compression and to obtain compression ratios without taking into account the usual compromise between firstly the compression ratio and secondly, the quality of the reconstruction.

Improvements of the transformations properties and algorithms are made regularly. One can quote as an example the transformationof Karhunen-Loèvemodified by Haralik and al. [21]. Usual algorithms of compression were used with diverse successes to compress the EMG signals [22], [23], [24], [25]. HemantAmhia and al in [26] compressed the speech by using successively the discrete wavelet transform and discrete cosine transform. Ntsama and al. [27] developed a new algorithm of compression of the EMG signals. This algorithm first performs the transformation of one-dimension (1-D) EMG signals totwo-dimension (2-D)

EMG signals. These 2-D data pass from time-space to wavelet-space and,after, to the frequency-space by using of successivelyDWT and DCT. Welba et al. [28] proposed a compression algorithm for EMG signals. It is based on the encoding of the 1-D EMG signals by the DPCM method followed by a transformation of the 1-D signal into a 2-D signal. The EMG signal successively undergoes the 2-D wavelet transform and the cosine transform. The coefficients obtained are coded by the SPIHT method. In a paper submitted for publication, we proposed a compression algorithm of EMG signals. This algorithm uses the decomposition of 1-DEMG signal by thediscrete wavelets packetstransform; the obtained coefficients are encoded by the DPCM method followed by Huffman coding. This work has yielded interesting results. However, the compression algorithm of the EMG signals, combining the DWPT on 1-D EMG signals and the processing coefficients in frequency space by the 1-D DCT, despite its potential has never been tried, hence the importance of this work.

B. Evaluation Parameters

Several parameters allow assessing an algorithm of compression. An enumerationof the most used is presented below.

The compression ratio is the goal of all compression methods. It is defined by:

$$\mathrm{CR} = \left(1 - \left(\frac{\text{Size of compressed file}}{\text{Size of original file}}\right)\right) \tag{1}$$

Howeveras said previously, the techniques which have highest compression ratios introduce more distortions on the signal. These distortions can be assessed by the relationships (2) to (5).

- The mean square error, which expresses the difference between original and the reconstructed denotedMSE (Mean Square Error).

$$\mathrm{MSE} = \frac{1}{\mathrm{N}}\sum_{n=1}^{\mathrm{N}}(s_0(n) - s_r(n))^2 \tag{2}$$

where: s_0 and s_r represent respectively the original and the reconstructed signal.

- The signal to noise ratio, which compares in the logarithmic scale the powers of the signal and the reconstruction error denoted SNR (signal to noise report).

$$\mathrm{SNR} = 10\log\left(\frac{\sigma_s^2}{\sigma_e^2}\right)\ (\mathrm{dB}) \tag{3}$$

with:

σ_s^2 is the spectral power of the original signal;

$\sigma_e^2$is the spectral power of the reconstruction error.

- The distortion of the mean frequency denoted MFD (Mean Frequency Distortion).

$$\mathrm{MFD} = \left(\frac{|F_{original} - F_{reconst}|}{\max(F_{original}, F_{reconst})}\right)^2 \tag{4}$$

where:

$F_{original}$ and $F_{reconst}$ represent the mean frequency calculated respectively on the frequency spectrum of the original and the reconstructed signal.

- The percentage of the square root of the remaining difference PRD (Percent Root mean square Difference).

$$\mathrm{PRD} = \sqrt{\frac{\sum_{n=0}^{N-1}\left(s(n) - \hat{s}(n)\right)^2}{\sum_{n=0}^{N-1}(s(n) - \mu)^2}}.100\% \tag{5}$$

with:

s(n) original signal,$\hat{s}(n)$reconstructed, N is the length of the original signal and μ is the reference value of the analog-digital conversion used for data acquisition s(n) (μ = 0, for test EMG).

III. Proposed Method

A. Choice of the Transformations Order

The two possible options are drawn atFig. 2. To make the choice of transformationsorder,one will use the 2 following schemes and compare the results obtained.

Fig. 2. Order of transformation: DCT-DWPT (left), DWPT-DCT (right)

To decompose the signals into discrete wavelet packet transform onewill use the following equations:

$$a[j-1,k] = \sum_{n} h[n-2k]\, a[j,n] \tag{6}$$

$$d[j-1,k] = \sum_{n} g[n-2k]\, a[j,n] \tag{7}$$

$$H(\omega) = \sum_{k} h[k]\, e^{-jk\omega} \tag{8}$$

$$G(\omega) = \sum_{k} g[k]\, e^{-jk\omega} \tag{9}$$

where:

$H(\omega)$is a low pass filter;

$G(\omega)$is a high pass filter;

$a[j-1,k]$are approximation coefficients;

$d[j-1,k]$are detail coefficients.

The signal reconstruction equation is given by the formula (10).

$$a[j,k] = \sum_{n} h[n-2k]\, a[j-1,k] + \sum_{n} g[n-2k]\, d[j-1,k] \tag{10}$$

And the discrete cosine transform is performed using the following relationships:

$$X_k = \sum_{n=0}^{N-1} x_n \cos\left[\frac{\pi}{N}\left(n+\frac{1}{2}\right)k\right] \qquad k= 0,\dots,N-1 \tag{11}$$

where:

N denotes the number of samples of the signal.

The coefficients at the output of each of these two series of transformations are used to construct two histograms shown in Fig.3 and Fig. 4.

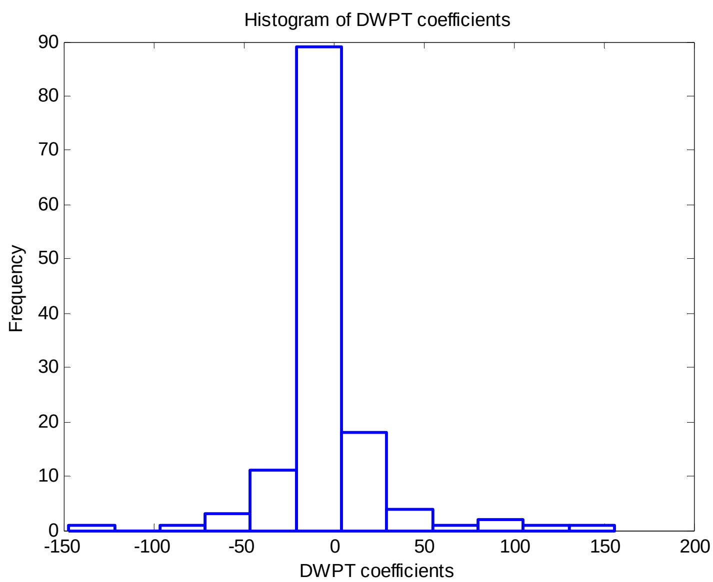

Fig.3. Histogram of DWPT coefficients in DCT domain

Fig.3 is obtained by constructing the histogram of the output coefficients of two transformations computed in the DWPT-DCT order. The histogram shows a concentration of more than 85 coefficients around zero. The amount of these coefficients for each interval decreases gradually as one move away from zero. One might think that a compression algorithm that combines in DWPT-DCT order can give good results. The confirmation of this hypothesis should be based on the quality of the reconstructed signal.

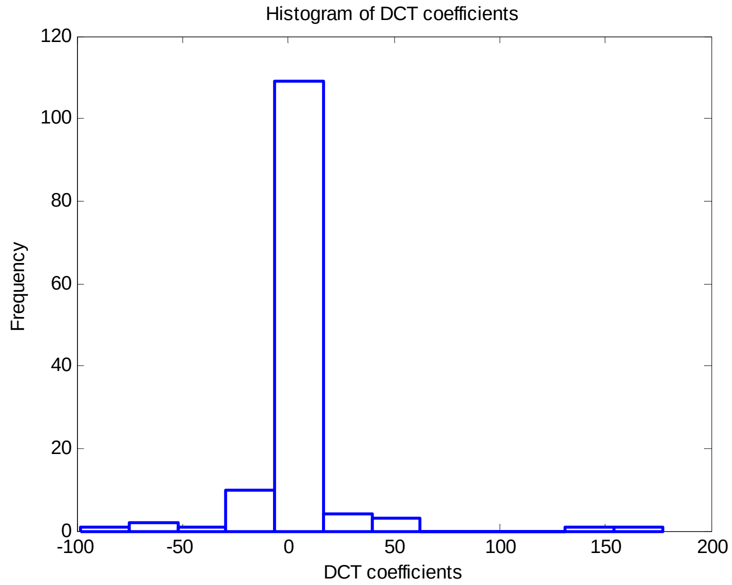

Fig.4. Histogram of DCT coefficients in the DWPT domain

Fig.4 is obtained by constructing the histogram of the output coefficients of two transformations placed in the following order: DCT then the DWPT. The results presented by the histogram show a concentration of more than 100 coefficients around zero. The amount of these coefficients for each interval decreases gradually as one move away from zero. It is noted in addition the disappearance of the coefficients contained in the range between 65 and 135. This very important loss factors will make sense in compression if we can reconstruct our signal in accordance of specifications. Observation of Fig.5 and Fig. 6, and Table 1 show that the DWPT-DCT order is the best.

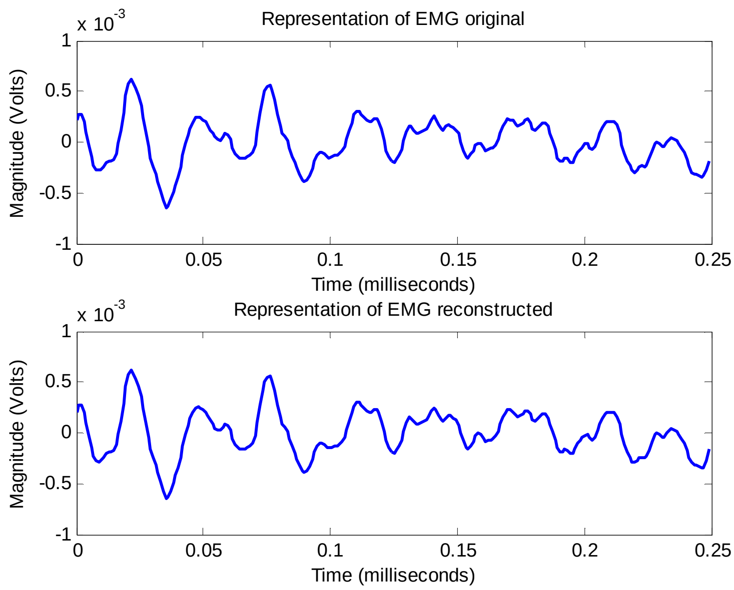

Fig.5. Compression by algorithm DWPT-DCT

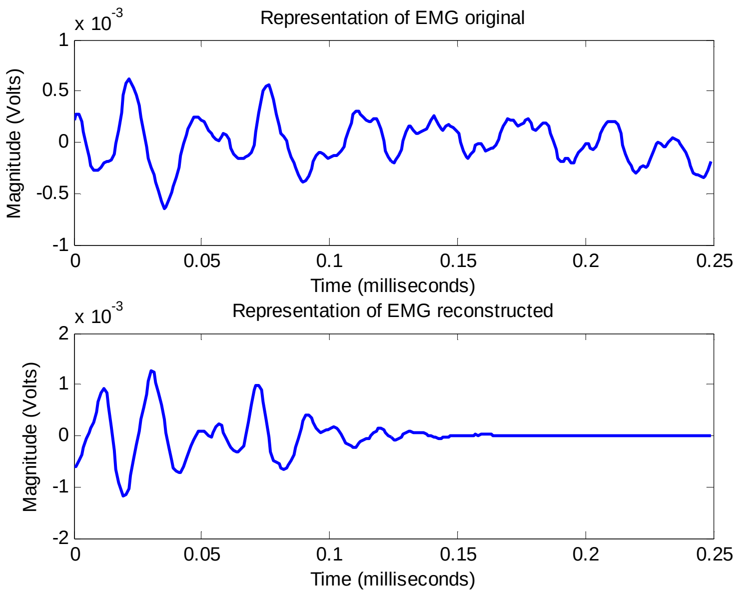

Fig.6.Compression by algorithm DCT-DWPT

TABLE 1. Summaries of Results in DWPT-DCT and DCT-DWPT Order

Transformations order	MSE	SNR	PRD
DWPT-DCT	1.8E-11	34.37	1.91
DCT-DWPT	1.20E-10	6.20	48.97

One observed both the two reconstructed signal and the different quality parameters produced by each of the two series of transformations. The DWPT-DCT alignment presents the reconstructed very close to the original signal. The other alignment (DCT-DWPT) does not lend itself to a compression application for sensitive data (medical data, for example). Reconstructing the data of a 0.25 millisecond window has not been possible in their entirety (Fig.6). Thus, in the work DWPT-DCT will be used.

B. Compression by our Approach

The scheme proposed is presented in Fig.7. The original EMG signal is whitened for the first time by DWPT. The conversion to discrete wavelet packet is defined by the following equations:

$$\left\{\psi_{l,n}^{k}(t) = 2^{\frac{l}{2}}\psi^{k}(2^{l}t - n), (l, n) \in (\mathbb{Z}, \mathbb{Z}), k \in \mathbb{N}\right\} \tag{13}$$

Thus, a function $s(t)$ of $L^2(\mathbb{R})$ may be decomposed on a basis of functions.

$$\left\{\psi_{l,n}^{k}(t), \ (l, n) \in (\mathbb{Z}, \mathbb{Z}): \ s(t) = \sum_{n,k} x_{k}^{l}(n)\psi_{l,n}^{k}(t)\right\} \tag{14}$$

The coefficientss$_k^l(n)$ at a scale l are determined by the following scalar product:

$$s_{k}^{l}(n) =< s, \psi_{l,n}^{k} >= \int_{-\infty}^{+\infty} f(t)\psi_{l,n}^{k}(t)dt \qquad (15)$$

The set of coefficientss$_k^l(n)$is called DWPT analysis of $s(t)$.

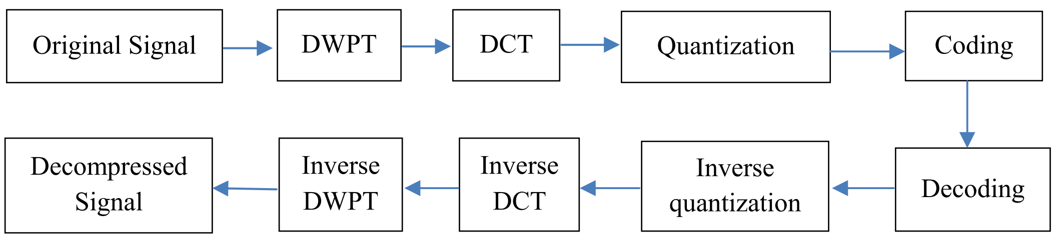

Fig.7.Compression diagram with double transformations

The DWPT greatly reduces the redundancy of EMG signal. The second bleaching is carried out by the DCT. This processing significantly improves the decorrelation and the thresholding of the data. The quantization makes it possible to reduce the number of bits for coding each coefficient.

IV. Analysis and Interpretation of Results

The method shown in Fig.7 has been implemented on an actual EMG signal. This is 8192 EMG points collected on a biceps and baptized Kheir1 from the initials of name of the person on which these recordings were made. One used the Daubechies wavelet of order four (db4). The results of this implementation were compared with those obtained by MAD method. The elements of this comparison are shown in Table 2 and Fig. 8.

TABLE 2. Evolution of Qualitative and Quantitative Parameters of the MAD and the Proposed Method (PM)

N°	MSE		SNR		PRD		MFD		CR	
	MAD	PM.	MAD	PM	MAD	PM.	MAD	PM.	MAD	PM
1	1.79E-11	1.83E-11	34.48	34.37	1.88	1.91	0.76%	0.76%	64.65%	68.68%
2	3.03E-11	3.02E-11	32.22	32.2	2.44	2.45	"	"	68.45%	72.52%
3	"	"	32.20	32.16	2.45	2.46	"	"	71.00%	75.19%
4	"	"	32.19	32.15	"	"	"	"	72.23%	76.36%
5	"	"	"	"	"	"	"	"	72.81%	76.95%
6	"	"	"	"	"	"	"	"	73.00%	77.18%
7	"	"	"	"	"	"	"	"	73.27%	77.40%
8	"	"	"	"	"	"	"	"	73.33%	77.50%
9	"	"	"	"	"	"	"	"	73.33%	77.63%
10	3.03E-11	3.06E-11	32.19	32.15	2.45	2.46	0.76%	0.76%	73.33%	77.63%

According to the results presented in Table 2, the use of DWPT associated to DCT as a tool to decorrelate the EMG signal, has made a significant improvement both in terms of qualitative (SNR, MSE and MDF) and quantitative parameters (compression ratio). Fig.8 shows the improvement of the resulting compression ratio.

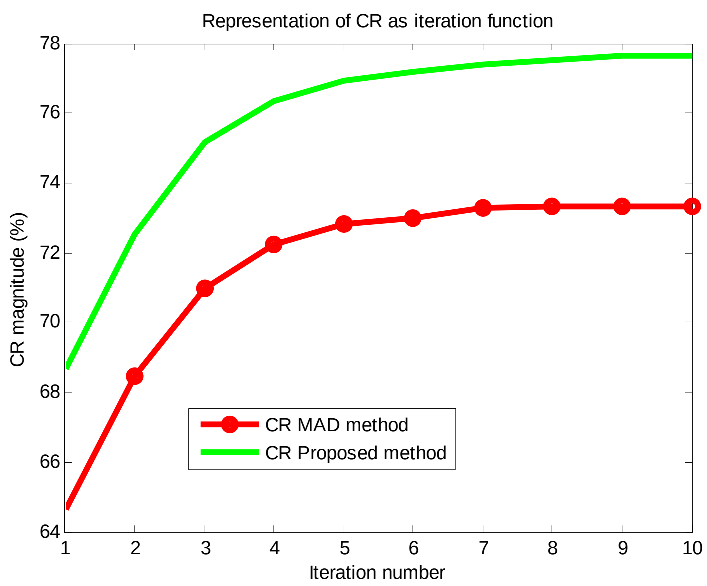

Fig.8.Evolution of compression ratio as a function of iterations number

This figure shows how the compression ratio is increasing in function of the number of iterations. The compression achieved by the method combining both DWPT and DCT is better compared to results obtained with MAD method. The EMG signal has been compressed and decompressed by MAD method and by the proposed method. A visual representation is given on in Fig.9 and Fig. 10.

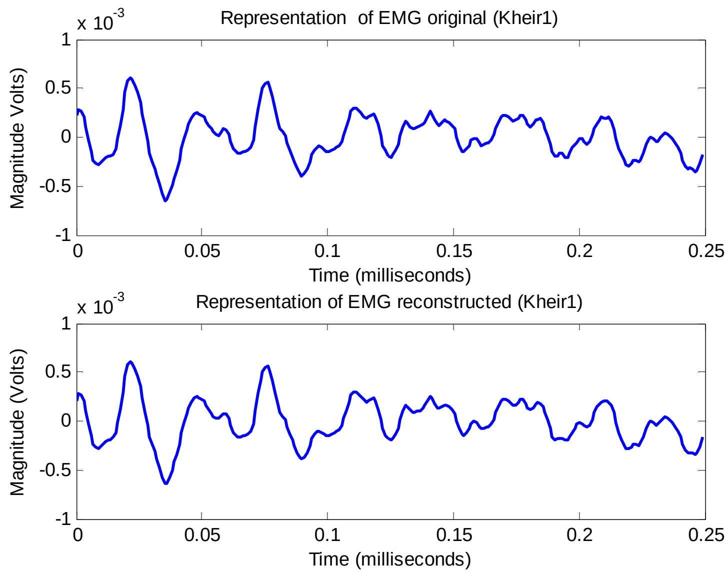

Fig.9.Compression and decompression by MAD method

The results in Fig.9were obtained after nine (9) iterations. The qualitative and quantitative parameters of the compression method are:

SNR=32.19 dB, MSE=3.06E-11, MDF=0.76% andCR=73.33%.

Despite the good quality of the reconstructed signal, the compression ratio remains less than that obtained by the proposed method presented in Fig. 10.

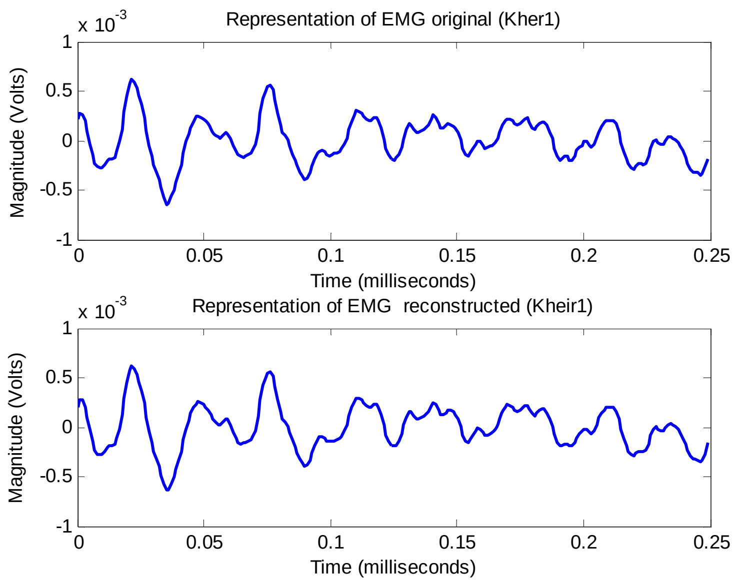

Fig.10. Compression and decompression by proposed method

Fig.10shows the reconstructed obtained after nine (9) iterations by proposed method. The qualitative and quantitative parameters of the compression method are:

SNR=32.15 dB, MSE=3.06E-11, MDF=0.76%,and CR=77.63%.

This confirms the subjective impression of the quality of the reconstructed signal.

V. Conclusion

In this article, the authors have implemented a new method of compression/decompression which outperforms the compression/decompression by the MAD method. For a given number of iterations, the compression ratio of the proposed method exceeds that of the method object of comparison by a value of 4.30%. The results are encouraging when taking into account the objective and subjective criteria (SNR, MSE, MFD, CR and visualobservation). These results can be achieved only if one aligns the transformations in the proper order for compression applications. So, one knows that for compression applications, it is easier to transform the wavelet space into frequency space and not the reverse. In future works,the use of more than two transformations in compression could constitute a runway of improvement of this algorithm.

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