

# Compression Approach of EMG Signal Using 2D Discrete Wavelet and Cosine Transforms

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**Abstract** The use of telemedicine is of paramount importance, and often involves the compression of biomedical signals. These signals are sensitive to many statistical parameters and high levels of compression, we propose in this work a new approach to compression of EMG signals. The Discrete Wavelet Transform (DWT) and SPIHT (Set Partitioning In Hierarchical Trees) coding proven, we propose to adapt this transform by associating the Discrete Cosine Transform (DCT). The idea is to transform the EMG signal in 2D by a technique so as to increase the correlation between pixels. The image thus formed is then segmented into blocks of pixels of size  $M \times N$ , where each block will undergo the Discrete Wavelet Transform or Discrete Cosine based on criteria that take into account some statistical parameters of order 1 or 2. The operation is repeated on all blocks of the image. The coefficients thus obtained are coded by the SPIHT coding. The results obtained allow reaching a good compromise between the PRD, the compression ratio and quality of reconstruction of the EMG signal.

**Keywords** Compression, Electromyogram 2D, Discrete Wavelet Transform, Discrete Cosine Transform, Statistical Parameters

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## 1. Introduction

Electromyography has a great important in pathological diagnostic, of patients suffering of neuromuscular disorders [1]. His record is called electromyogram[1-3]. When this recording is quite long in time, it happens a crucial problem of storage and transmission through telecommunications networks especially for remote operations or diagnostic aid. Because real time transmission requires high speed, compression remains the most appropriate approach to solve this problem. The purpose is to find the best compromise between speed transmission and signal reconstruction to avoid any degradation that may lead to fatal diagnostic[4]. To achieve such a result, literature offers two types of compression: Lossy compression which often includes quantification stage to improve the compression ratio and lossless compression that gives a good signal reconstruction but which hardly yields high compression ratio[5],[6]. In this work, we are using the lossless compression.

The approach that we propose consists in using the technical image for EMG signal compression, while exploiting the DWT and DCT. In our work we propose to set

EMG signal into 2D by a design technical while exploiting the work of Marcus and al.[7], to increase the correlation between pixels and better handling parameters in image mode. Obtained image is parted into blocks of size  $M \times N$ . Each block will undergo the Discrete Cosine Transform (DCT)[8] and the Discrete Wavelet Transform (DWT)[9]. The transform which present better statistical parameters (entropy) will be keep for that block. All images blocks will then be processed on that way. At the end of this operation, SPIHT encoder[10],[11] is applied. This paper is organized as follows, in Section 2, we present used equipment and uses of statistical parameters, in Section 3, details on EMG signal into 2D and compression approach are describe. Obtained results are given in section 4, and followed by a conclusion.

## 2. Background

In this section, DWT, DCT, SPIHT coding and statistical parameters are concepts that we have used to work. An Overview of Wavelet Transform and Cosine Transform are presented.

### 2.1. Wavelet Transform

Wavelet transform analyses signals in both time and frequency domain simultaneously. This method has proved to be very powerful techniques for signal compression.

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Discrete wavelet transform is a multi-resolutions/multi-frequency representation[1],[12].

The 2D DWT is built with separable orthogonal mother wavelets, having a given regularity. At every iteration of the DWT, the lines of the input image are low-pass filtered with a filter having the impulse response  $g$  and high-pass filtered with the filter  $h$ . Then the lines of the two images obtained at the output of the two filters are decimated with a factor of 2. Next, the columns of the two images obtained are low-pass filtered with  $g$  and high-pass filtered with  $h$ . The columns of those four images are also decimated with a factor of 2. Four new sub-images are generated. The first one, obtained after two low-passes filtering, is named approximation sub-image. The others three types of detail coefficients and basis functions are named: horizontal detail, vertical detail and diagonal detail. The approximation image represents the input for the next iteration.

The coefficients are computed using the following relation:

$$a_{j,m,n} = \iint \phi_{j,m,n}(x,y) emg(x,y) dx dy \quad (1)$$

$$d_{j,m,n}^v = \iint \psi_{j,m,n}^v(x,y) emg(x,y) dx dy \quad (2)$$

$$d_{j,m,n}^h = \iint \psi_{j,m,n}^h(x,y) emg(x,y) dx dy \quad (3)$$

$$d_{j,m,n}^d = \iint \psi_{j,m,n}^d(x,y) emg(x,y) dx dy \quad (4)$$

Where  $a_{j,m,n}$ ,  $d_{j,m,n}^v$ ,  $d_{j,m,n}^h$ ,  $d_{j,m,n}^d$  represents the approximation coefficients at level  $j$ , the vertical, horizontal and diagonal detail coefficients respectively.

$\phi(x,y)$  is the scale function and  $\psi(x,y)$  is the mother wavelets.

$$\phi_{j,m,n}(x,y) = 2^{-j} \phi(2^{-j}x - m, 2^{-j}y - n) \quad (5)$$

$$\psi_{j,m,n}(x,y) = 2^{-j} \psi(2^{-j}x - m, 2^{-j}y - n) \quad (6)$$

The reconstruction is done using quadrature mirror filters, represented by their impulse responses ( $h$  and  $g$ )[9],[13]. This reconstruction reverse the decomposition operation (replacing the low-pass filters and high pass filters with their associated mirrors) and decimation operation is replaced by interpolating operation which add a zero between each pair of coefficients.

## 2.2. Discrete Cosine Transform

The discrete cosine transform is a linear transformation similar to the discrete Fourier transform. It provides good decorrelation of samples strongly linked. It concentrates information and makes it so usable for image compression, as used by the old JPEG standard[8]. DCT has several advantages: It is real and can be computed using a fast algorithm. On the other hand, coefficients are well decorrelated in transform domain. It has an excellent concentration of energy for highly correlated data. In our approach, 32 x 32 sized windows are used for a high reduction of data by SPIHT encoder.

The 2D- Discrete Cosine Transform is a direct extension of the 1-D and is given by:

$$B_{pq} = \alpha_p \alpha_q \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} A_{mn} \cos\left(\frac{\pi p(2m+1)}{2M}\right) \cos\left(\frac{\pi q(2n+1)}{2N}\right) \quad (7)$$

With  $0 \leq p \leq M-1$  et  $0 \leq q \leq N-1$

The inverse Transform is defined as:

$$A_{mn} = \sum_{p=0}^{M-1} \sum_{q=0}^{N-1} \alpha_p \alpha_q B_{pq} \cos\left(\frac{\pi p(2m+1)}{2M}\right) \cos\left(\frac{\pi q(2n+1)}{2N}\right) \quad (8)$$

With  $0 \leq m \leq M-1$  et  $0 \leq n \leq N-1$

$$\alpha_p = \begin{cases} \frac{1}{\sqrt{M}} & \text{if } p=0 \\ \sqrt{\frac{2}{M}} & \text{if } 1 \leq p \leq M-1 \end{cases} \quad \text{and} \quad \alpha_q = \begin{cases} \frac{1}{\sqrt{M}} & \text{if } q=0 \\ \sqrt{\frac{2}{M}} & \text{if } 1 \leq q \leq N-1 \end{cases}$$

$A_{mn}$  represents a value of initial image for a given  $m$  and  $n$ .  $B_{pq}$  represents DCT coefficients and  $M \times N$  represents size of an image block.

## 2.3. Statistical Parameters

To choose the most appropriate transform on each part of the image, we check their statistical parameters[14]. These are mathematical equations that assess signal quality. Images are more sensitive, to entropy and variance. Autocorrelation is used to increase the relationship between pixels. Entropy allows us to determine the amount of information contained in an entity. It is also used to evaluate the disorder. The decorrelation characteristics should render a decrease in the entropy of an image. This will, in turn, decrease the number of bits required to represent the image. This is a reason the entropy has been chose. Thus, Transform coefficients which have minimal entropy are selected to perform considered pixels block. Entropy is defined as:

$$H(X) = - \sum_{i=1}^N p(x_i) \log(p(x_i)) \quad (9)$$

Where  $P(x_i)$  is the value of the probability mass function at  $X = x_i$ .

## 2.4. SPIHT Coding

Coding plays an important role in compression. SPIHT coding, as its name suggests respects a tree branches hierarchy coding[10]. Order in which pixels are presented to significance test are managed by two linked lists, the one of non-significance pixels (List of Insignificant Pixels: LIP) and the one of insignificant subsets (List of Insignificant Sets: LIS). A third linked list manages significant pixels (List of Significant Pixels: LSP). List LIS elements can have two possibilities: type A, corresponding to all descendants of a node, or type B, corresponding to all descendants of a node except its four children. During sorting step, significance test is first applied to all elements of list LIP, then to those of list LIS, from first to last. Lists are modified as follows: if a subset of B becomes significant, it is divided into four subsets of type A that are added to the end of LIS list. If a subset of type A (associated to a node  $i$ ) becomes significant, it is divided into four pixels (children of  $i$ ). The significance

test is applied to each of them before adding them to the end of LIS or LSP lists. If children have descendants, two cases are possible if set B associated with node  $i$  is not significant, it is then added to the end of LIS list or if it is significant, the four types A subsets associated with  $i$  children are then added to the end of LIS list.

The SPIHT coding[11],[15] that we used has been slightly modified on its value  $S_k(X_i)$ . Using both DWT and DCT introduced a sizing bug during encoding. The profit is that each part of our image can be considered as a detail or not according to threshold value. In the following equation,  $k$  is the number of coefficients to encode and  $S_k$  the importance of pixel  $X_i$  as approximation or detail:

$$S_k(X_i) = \begin{cases} 1 & \text{if } |X_i| \leq \frac{2^k}{k} \\ 0 & \text{if } |X_i| > \frac{2^k}{k} \end{cases} \quad (10)$$

With  $k = \lfloor \log_2(\max_i |X_i|) \rfloor$  where  $0 \leq i \leq k$

### 3. Proposed Approach

Images encoding algorithms can be used on one-dimensional signals, if samples are set into 2D. This approach has been usually used in ECG signal compression studies. Thus, Lee and Buckley in 1996[16],[17], Uyar and Ider in 2001[18] proposed methods for ECG signal compression based on two-dimensional Discrete Cosine Transform. Moghaddam and Nayebi[19], Bilgin and al.[20] presented another approach for ECG signal compression using wavelets and set of wavelet. 2D encoding methods based on Discrete Wavelet Transform and SPIHT coding has been previously proposed[21-25]. But, just a few works has been published in the case of EMG signal into 2D[7]. Most of works on EMG signal compression are based on one dimensional model. Norris and al.[26] using adaptive differential pulse code modulation. Guerrero and al.[27] compared differential compression methods. Welling and al.[28], Norris and al.[29] using EZW for compression EMG. Berger and al.[2] proposed an algorithm for EMG compression using wavelet transform, Paiva and al.[30] proposed adaptive EMG compression using optimized wavelet filters. We also have work of Filho and al.[3], Ntsama and al.[31, 32].

#### 3.1. EMG Signal into 2D

To set EMG signal into 2D, several methods are combined to yield a strongly correlated image. We first find an approximation of our image with a first order polynomial summation. EMG signal is parted in  $M_i$  sequences multiple of 128, then align each after other and fulfill with zeros if necessary (zeros will be automatically removed during reconstruction) to give back sequence  $M_N$ . Objective here is to achieve a 2D matrix of size  $M \times N$  ( $M = N$ ).

Let  $x$  be multiple of EMG signal. If  $x$  is multiple of 128 ( $128 * N = 2k$ , where  $k = 1 \text{ or } 2$ ), then sequence  $M_i$  is given by:

$$M_i = \sum_{j=1}^N x(k + N * (i-1)) \text{ with } i \in \{1, 2, 3, 4, \dots, N\} \quad (11)$$

If  $x$  is not multiple of 128, then sequence  $M_i$  is given by:

$$M_i = \sum_{j=1}^N x(k + N * (i-1)) \text{ with } i \in \{1, 2, 3, \dots, N-1\} \quad (12)$$

And the last sequence is given by:

$$M_N = [R_N, \text{Zero}(n)] \text{ with } R_N = M_N - \text{Zero}(n) \quad (13)$$

$R_N$  is remaining sequence which is different of  $M_i$  and  $\text{Zero}(n)$  is the number of zeros addition to supplement  $R_N$ .

During the second step, lines are classifying according to their autocorrelation coefficients. The first line is followed by the nearest one (autocorrelation coefficients). We consider the second line as the first and the same process is reiterated until the end of 2D EMG. Figure 1 gives an illustration of that process.

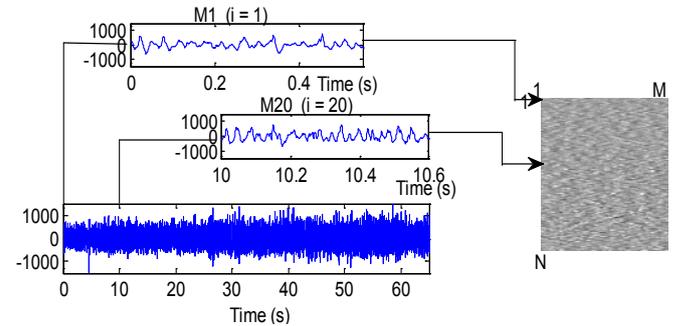


Figure 1. EMG signal process in 2D

Correlation coefficients  $R(u,v)$  are calculated through work of Marcus and al.[7] by the following formula:

$$R(u,v) = \frac{C(u,v)}{\sqrt{C(u,u) * C(v,v)}} \quad (14)$$

Where  $C$  is covariance matrix;  $u$  and  $v$  two different lines.

Figure 2 shows 2D EMG signal named Kheir1 before and after correlation process.

#### 3.2. Compression Approach

A block diagram of compression process is shown in Figure 3. The method consists in segmenting EMG signal into 512 or 128 sample windows and arranging these segmenting as different columns of a 2D matrix. Once EMG image is obtained, compression process can start. Image is divided into pixel blocks of size  $32 \times 32$ , in order to reduce noise and errors over a large portion of the signal. Processing that way also significantly reduces compression and decompression. Each block undergoes DWT and DCT and our algorithm only retains coefficients of the transform which yield best statistical parameters. All image blocks undergo the same technique. SPIHT coding is finally applied on chosen coefficients. At the end, the reverse process is applied, to have an accurate reconstruction of original signal.

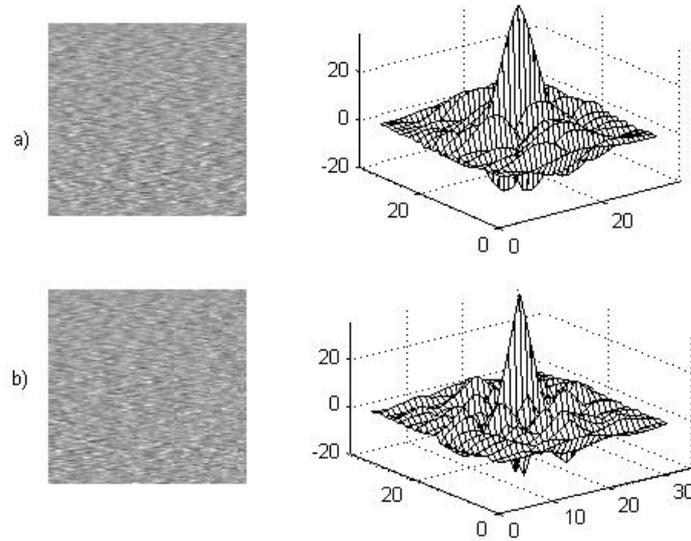


Figure 2. Comparison EMG signal and associated autocorrelation function: a) before correlation ; b) after correlation

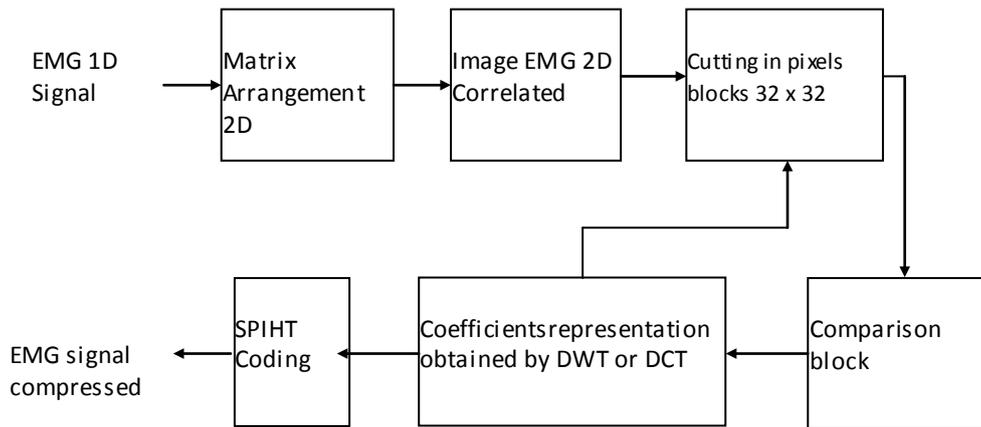


Figure 3. Block diagram of the proposed approach compression

During comparison stage, we retain the coefficients which check the following relation:

$$coefficients = \begin{cases} DWT \text{ coefficients if statistical parameters better} \\ DCT \text{ coefficients else} \end{cases} \quad (15)$$

### 4. Results and Discussion

Reconstruction quality is measured by signal to noise ratio (SNR) and percentage root mean square difference (PRD). These criteria are defined as follow:

→PRD is the most used in majority of scientific works and can be defined as[33]:

$$PRD = \frac{\sqrt{\sum_i (x_{org}(n) - x_{rec}(n))^2}}{\sqrt{\sum_i (x_{org}(n))^2}} \times 100 \quad (16)$$

$x_{org}$  original signal and  $x_{rec}$  reconstructed signal.

PRD is linked to SNR by a negative logarithmic function:

$$SNR = -20 \log_{10} (0.01 \times PRD) \quad (17)$$

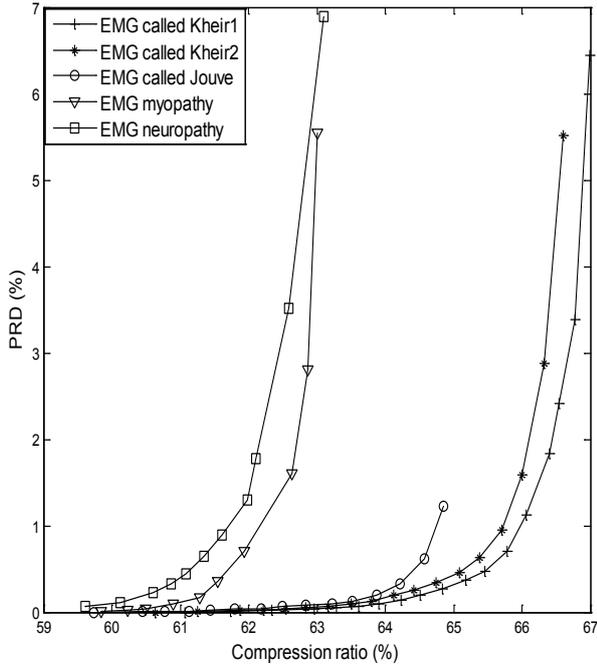
→The measure of compression is obtained from the compression ratio (CR) is defined as:

$$CR = 100 \times \left( 1 - \frac{\text{compressed size}}{\text{original size}} \right) \quad (18)$$

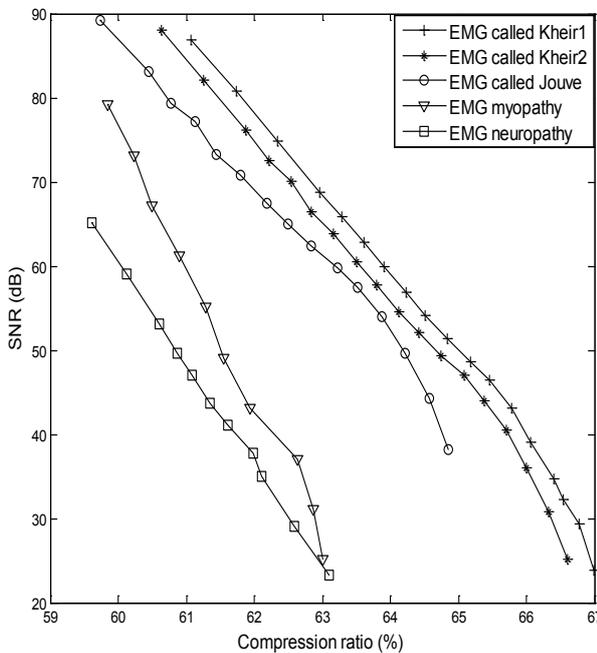
Proposed method was evaluated on actual EMG data. Tests were performed on three EMG signals Kheir1, Kheir2 and Jouve. The signals were amplified with a total gain of 2000, and sampled at 2024 Hz using a 12 bits data acquisition. Signals were measured on the biceps muscle. The signals were collected during 40%MVC contraction, with an angle of 90° between the arm and the forearm. We also used EMG signal obtained from Beth Israel Deaconess Medical Center data base[34]. For signal named emg\_healthy, we considered 16384 samples (128 x 128 for 2D-EMG) and for other signals, we considered 262144 samples (512 x 512 for 2D-EMG). Wavelet chosen for DWT is bi-orthogonal 4-4[35] to have good results. Compression quality is evaluated by the PRD, SNR(signal to noise ratio) and CR(compression ratio).

Figures 4 and 5 show variations of compression ratio as a function of SNR and PRD for Kheir1, Kheir2, Jouve, emg\_healthy and emg\_neuropathy EMG signals. It appears

that PRD increases with compression ratio while SNR decreases. Reconstruction quality is good if the PRD is close to zero. At high compression ratio, energy relative error is large.



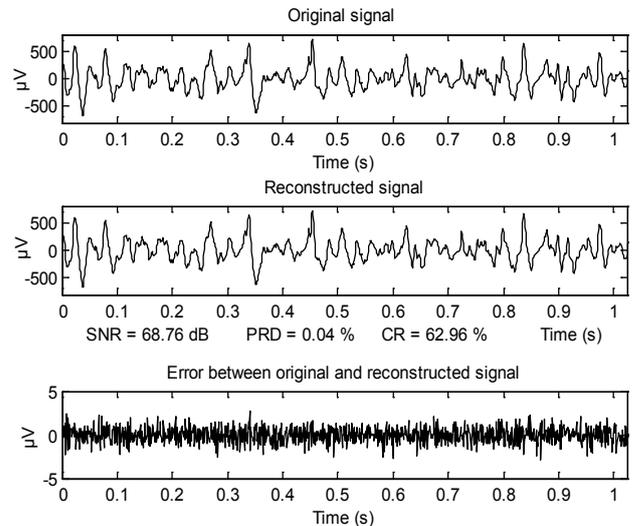
**Figure 4.** Variation of the PRD as a function of the compression ratio



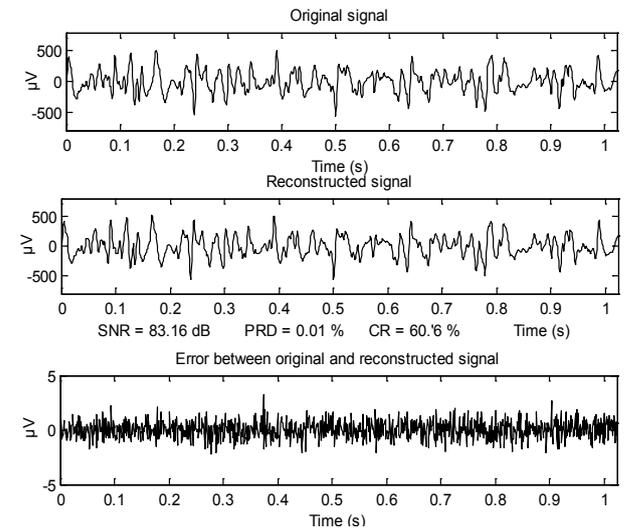
**Figure 5.** Variation of the SNR as a function of the compression ratio

Figures 6, 7, 8 and 9 show some examples of original and reconstructed signals for different EMG. The compression ratio is 61 % for a PRD is 0.01 % and SNR is 83 dB for a rate bits by pixel of 7 (Kheir2 and Jouve). With this compression ratio, signal degradation is not perceptible. A comparison of our results with those obtain before by Berger and al.[2], Norris and al.[29],Ntsama and al.[31], Ele and al.[32], Marcus and al.[7] or Filho and al.[3], shows a significant

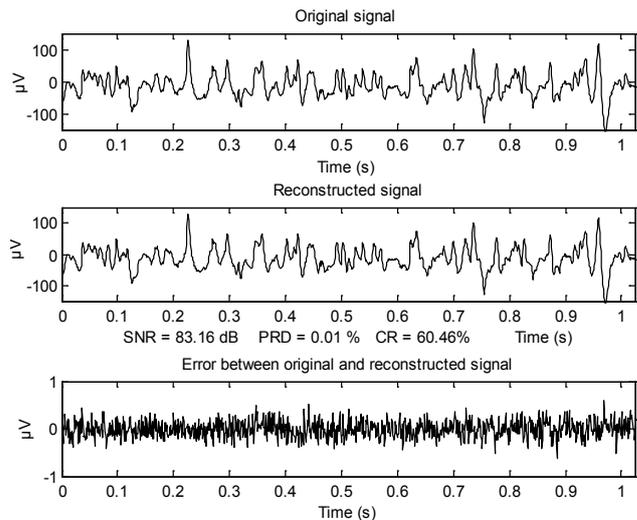
improvement of PRD.



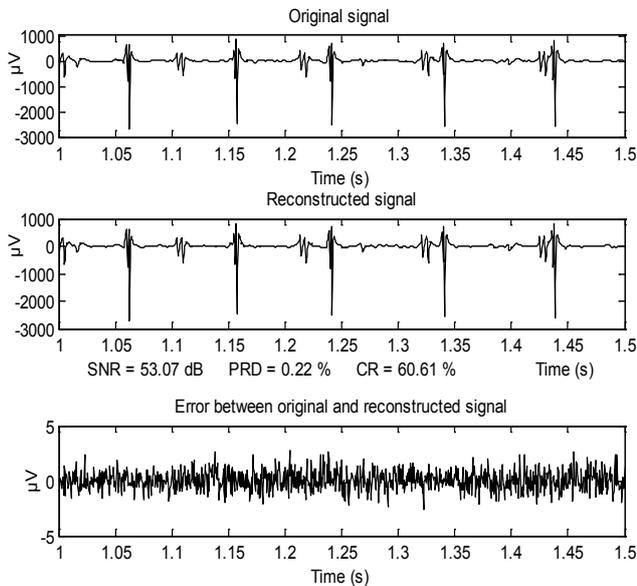
**Figure 6.** Reconstruction of EMG signal called Kheir1 for a rate bits by pixel of 7



**Figure 7.** Reconstruction of EMG signal called Kheir2 for a rate bits by pixel of 7



**Figure 8.** Reconstruction of EMG signal called Jouve for a rate bits by pixel of 7



**Figure 9.** Reconstruction of EMG neuropathy signal for a rate bits by pixel of 9

## 5. Conclusions

In this paper we have shown that it is possible to optimize and improve compression performance of an EMG signal by setting it into a 2D signal and use statistical parameters in order to apply on each part of EMG image the most appropriate transform. This method has been applied to different signals and develops a pretty good tolerance to high compression ratios while keeping acceptable PRD. There is hope in obtained results according to objective and subjective criteria. Uses of this method, will increase storage space and transmission speed on telecommunications lines. Beside this, it would be interesting to study how does a noisy digital channel will damages the signal, and then improve results.

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