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Exploitation of Differential Pulse Code Modulation for Compression of EMG Signals by a Combination of DWT and DCT

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Abstract Storage and transmission of medical information are for more than a decade a subject of great importance, particularly because of exponential growth experienced by telemedicine. This paper presents a compression method of EMG signals, based on Differential Pulse Code Modulation (DPCM) encoder as pre-processing. The method consists to process a signal by the DPCM coder and transform signal into 2D, arrange this signal by correlation sorting function and cut it into blocks of pixels. Finally, we apply Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT). The coefficients thus obtained are coded by the SPIHT coding. The results obtained on actual signals are evaluated by the compression ratio (CR), the signal to noise ratio (SNR), percentage root mean square difference (PRD) and quality of reconstruction EMG signal. This method offers encouraging results in terms of Compression Ratio (CR) and PRD.

Keywords Compression, EMG, DCT, DPCM, SPIHT, DWT

1. Introduction

Images, as the electrophysiological signals contain redundant information. The aim of compression is to minimize or eliminate such redundancy. The compression of electrophysiological signals is the subject of many studies that focus on improvement of compression algorithms and the development of new techniques and compression formats. Predictive coding also called Differential Pulse Code Modulation (DPCM) is a simple method for reduction of redundancy [1, 2]. The hidden theory of predictive coding is to predict the sample values of a signal based on previous values, and coding the prediction error. That is why we proposed to significantly reduce signal distortion by the predictive coding in order to obtain a low value of the percentage root mean square difference in compression.

Compression of electrophysiological signals in 2D began with the electrocardiogram (ECG) signals, before extending to others as EMG. In this review, just a few works will be mentioned to show the exponential growth of this technique. Lee and Buckley in 1996 [3, 4], and Uyar *et al.* 2001 [5] proposed compression methods of electrocardiogram (ECG) signals based on discrete cosine transform 2D.

Moghaddam and Nayebi [6], Bilgin et al. [7] presented another approach for the compression of ECG signal based on the discrete wavelet transform.The methods based on 2D coding on the discrete wavelet transform and SPIHT coding have been previously proposed [8, 9, 10]. The literature shows some works on the compression of EMG signal in 2D [11]. Most of works on compression of EMG signals are based on 1D model. Norris et al. [12] used Adaptive Differential Pulse Code Modulation. Guerrero et al. [13] compared different methods of EMG compression. Welling et al. [14] and Norris et al. [15] used Embedded Zerotree Wavelet (EZW) for compression of EMG signal. Berger et al. [16] proposed an algorithm for compression of EMG based on discrete wavelet transform. Paiva et al. [17] proposed adaptive compression of EMG using optimization wavelet filters. The work of Filho et al.[18] are based on compression of EMG signals using recurring models; Ntsama et al [19, 20] used fractals, associated Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) SPIHT coding to compress EMG.

The original EMG signal is transformed into an image (matrix). The obtained image is treated as an ordinary image. This compression technique has proven itself in terms of good results [11, 19, 20, 21]. Discrete Cosine Transform (DCT) has a great concentration of energy for highly correlated data [22]. Discrete Wavelet Transform is a widely used tool in signal processing. One of its main

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applications is image compression, because of its capacity to compact the energy in a small number of coefficients which leads to an efficient coding of image. Because of these advantages, we used DWT or DCT by taking the parameters which best adapt to algorithm so as to compress the EMG signal. SPIHT coding is finally applied. The obtained results are encouraging and provide many perspectives. The paper is organized as follows: in section 2, we describe Differential Pulse Code Modulation encoder (DPCM), Discrete Cosine Transform and Discrete Wavelet Transform and Set partitioning In Hierarchical Trees coding (SPIHT). In section 3, compression approach is described. Obtained results are given in section 4, and followed by a conclusion.

2. Background

2.1. Differential Pulse Code Modulation (DPCM)

The principle of DPCM (Differential Pulse Code Modulation) coding is to make a numerical prediction of the signal to be code. The difference between each sample and the respective estimated value for this sample is coded. The predictive coding theory is to predict the values of samples of a signal and to encode prediction error. Figure 1 illustrates a block DPCM coder, where the difference between input samples and those predicted, is quantized and encoded for transmission. As for decoder, the error signal received is added to predicted signal. There are several forms of predictors. In this paper, we use the linear predictor of order N on 1D signal.

If $\tilde{x}(n)$ is predicted signal and $x(n)$ the original signal, linear predictor is following form:

$$\tilde{x}(n) = \sum_{i=1}^{N} h_i\left(x(n-i)\right) \tag{1}$$

With $h = \left(h_1,\ h_2, \ldots, h_N\right)^t$

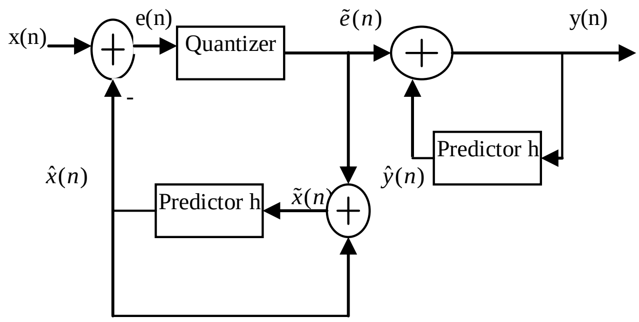

Figure 1. Diagram block of DPCM coding

From figure 1, we have the following equations:

$$\begin{aligned} q(n) &= \tilde{e}(n) - e(n) \\ e(n) &= x(n) - \hat{x}(n) \\ \tilde{x}(n) &= \tilde{e}(n) + \hat{x}(n) \\ y(n) &= \tilde{e}(n) + \hat{y}(n) \end{aligned} \tag{2}$$

2.2. Discrete Cosine Transform

The compression methods of EMG signals based on DCT admit an orthogonal transformation that is applied to the original signal. The redundancy of the signal in the new representation is reduced by means of existence of efficient algorithms for calculation. DCT has several advantages: it is real and can be calculated using a fast algorithm (hence its easy implementation). On the other hand, coefficients are decorrelated in the transformed domain. It has an excellent energy concentration for highly correlated data [20]. It tends to concentrate information, and thus making exploitable for image compression as used by the former JPEG standard [20]. In this paper, Discrete Cosine Transform in dimension 2 is applied to EMG transformed into 2D. The 2D DCT is given by the following formula:

$$H(u,v) = \frac{2}{\sqrt{MN}} C(u)C(v) \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} h(x,y)\cos\left(\frac{\pi u\left(2x+1\right)}{2M}\right)\cos\left(\frac{\pi v\left(2y+1\right)}{2N}\right) \tag{3}$$

The inverse Transform of DCT process is defined as:

$$h(x,y) = \frac{2}{\sqrt{MN}} \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} C(u)C(v)H(u,v)\cos\left(\frac{\pi u\left(2x+1\right)}{2M}\right)\cos\left(\frac{\pi v\left(2y+1\right)}{2N}\right) \tag{4}$$

With

$$C(\gamma) = \begin{cases} \frac{1}{\sqrt{2}} & \text{for } \gamma = 0 \\ 1 & \text{for } \gamma > 0 \end{cases} \tag{5}$$

M x N represents size of an image block.

2.3. Discrete Wavelet Transform

Discrete Wavelet Transform is a multiresolution / multifrequency representation [23, 24, 25, 26]. It is a tool that decomposes image into several sub-bands in three different directions: horizontal, vertical and diagonal. 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 [27, 28]. Finally, we have:

$$H(\omega) = \sum_k h[k] e^{-jk\omega} \qquad G(\omega) = \sum_k g[k] e^{-jk\omega} \tag{6}$$

Where H (ω) and G (ω) must be orthogonal:

$$|G(\omega)|^2 + |H(\omega)|^2 = 1 \tag{7}$$

The coefficients obtained are:

$$c[\text{j-1,k}] = \sum_n h[n-2k]\, c[\text{j,n}] \qquad d[\text{j-1,k}] = \sum_n g[n-2k]\, c[\text{j,n}] \tag{8}$$

The reconstruction of original signal is given by following formula:

$$c[j,n] = \sum_k h[n-2k]c[j-1,k] + \sum_k g[n-2k]d[j-1,k] \tag{9}$$

2.4. SPIHT Coding

Coding plays an important role in compression. SPIHT coding [22] is used. Its advantage depends on the threshold value, where each part of image can be seen or not as a detail. SPIHT coding was developed by Said and Pearlman in 1996 [29,30]. This algorithm is an improvement of EZW proposed by Shapiro and is partitioned into three lists of coefficients.

1. List of Significant Pixels (LSP)
2. List of Insignificant Pixels (LIP)
3. List of Insignificant Sets (LIS)

The wavelet coefficients and trees are grouped into sets based on their significance information. Coefficients at the top of the pyramid have a strong spatial relationship with their children. The structure of coding SPIHT is represented by figure 2.

A wavelet coefficient at location *(i,j)* in the pyramidal representation has four offspring at locations:

$$O(i,j)=\{(2i,2j),(2i,2j+1),(2i+1,2j),(2i+1,2j+1)\} \tag{10}$$

This pyramidal structure is called spatial orientation tree.

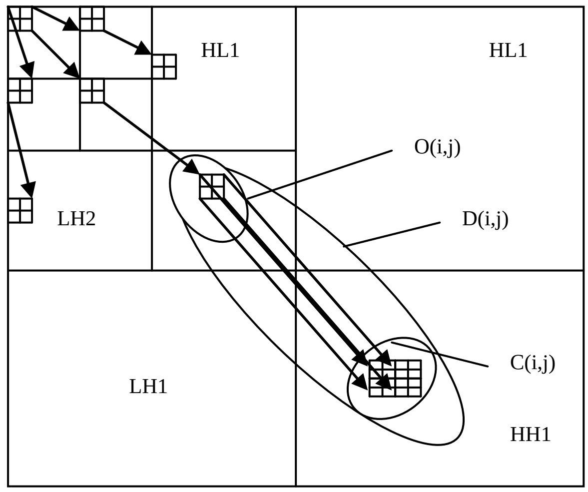

Figure 2. Offspring dependencies in the pyramidal structure

The encoding consists of two main stages:

- Sorting
- Refinement

SPIHT considers two different types of trees:

- Type A, where all descendants are not significant;
- Type B, where all descendants except the children are not significant.

Algorithm:

1. Initialization:

- Set LSP as empty list
- Add all coefficients without any parents to LIP
- Add all coefficients with descendants to LIS as type A.

2. Sorting:

For each entry *(i,j)* of the LIP:

- Output $S_n(i,j)$.

$$Sn(i,j) = \begin{cases} 0 \ \textit{if all descendants of } (i,j) > \textit{threshold} \\ 1 \ \textit{otherwise} \end{cases}$$

- If $S_n(i,j)$ is 1, move *(i,j)* to the LSP and output the sign of wavelet coefficient $C_{i,j}$.

For each entry *(i,j)* in LIS do and if the entry is of type A then

- Output $S_n(D(i,j))$.
- If $S_n(D(i,j))$ is 1 then for each (k,l) ∈ O(i,j) *instructions*
- Output $S_n(k,l)$
- If $S_n(k,l)$ is 1 then add *(k,l)* to the LSP and output the sign of $C_{k,l}$ else add *(k,l)* to the end of LIS as entry of type B and go to step 2; else remove entry *(i,j)* from the LIS.

If the entry is of type B then

- Output $S_n(L(i,j))$
- If it is 1 then add each (k,l) ∈ O(i,j) to the end of LIS as entry of type A.
- Remove *(i,j)* from LIS.

3. Refinement Pass:

For all entries *(i,j)* in the LSP except those included in the last sorting pass, output the n[th] most significant bit of $C_{i,j}$.

4. Decrement n and go to step 2.

O(i,j) - set of coordinates of offspring *(i,j)*.
D(i,j) - Set of coordinates of all descendants *(i,j)*.
H(i,j)- Set of all tree roots in highest level of pyramid.
L(i,j)=D(i,j)-O(i,j)

3. Proposed Approach

3.1. EMG Signal into 2D

The EMG signal in 2D is performed according the following algorithm:

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 $M \times N$ $(M = N)$.

If x is multiple of 128 ($128*N = 2k$, where $k = 1$ or 2), then sequence M_i is given by:

$$M_i = \sum_{j=1}^{N} X\left(k + N*\left(i-1\right)\right) \tag{11}$$

With $i \in \{1,2,3...,N\}$

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

$$M_i = \sum_{j=1}^{N} X\left(k + N*\left(i-1\right)\right) \tag{12}$$

With $i \in \{1,2,3...,N\text{-}1\}$

And the last sequence is given by:

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

R_N is remaining sequence which is different from of M_i and *Zero(n)* is the number of zero 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 (autocorrelation coefficients). We consider the second line as the first and the same process is reiterated until the end of 2D EMG. The correlation of coefficients was calculated in [11, 31], by the relation:

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

Where C is a covariance matrix, u and v are two different lines.

3.2. Compression Scheme

A bloc diagram of compression process in shown in figure 3. EMG signal 1-D is processed by DPCM coding, reducing much redundancy of signal before switching to compression method. The method consists to segmenting EMG signal into 512 or 128 sample windows and arranging these segmenting as different columns of a 2D. Once EMG image is obtained, compression process can begin. Image is divided either into pixel blocks of size 32 x 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 DCT and DWT and our algorithm only retains coefficients of the transform which yield best statistical parameters (entropy). It is advisable to choose parameters most sensitive and adapted to the program. All image blocks undergo the same technique. SPIHT coding is finally applied on selected coefficients. At the end, the reverse process is applied, to have an accurate reconstruction of original signal.

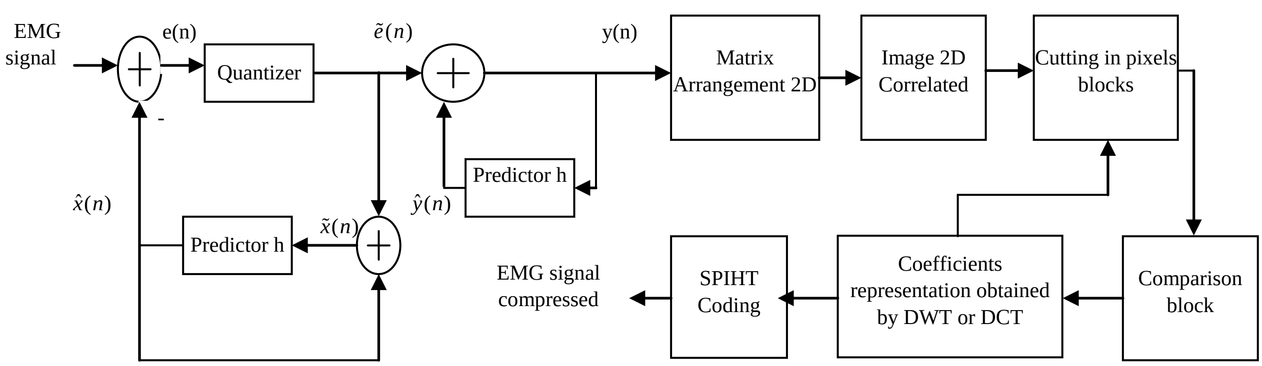

Figure 3. Block diagram of the proposed approach compression

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:

- The PRD is the most used in majority of scientific works and is defined as [32, 33, 34]:

$$PRD = \frac{\sqrt{\sum \left(x_{org}(n) - x_{rec}(n)\right)^2}}{\sqrt{\sum \left(x_{org}(n)\right)^2}} \times 100 \tag{15}$$

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

- Signal to noise ratio is calculated by:

$$SNR = 10\log\left(\frac{\sigma_s^2}{\sigma_e^2}\right) \tag{16}$$

With σ^2_s is power of original signal and σ^2_e is power of error

- The measure of compression is obtained from the compression ratio (CR), it is defined as [35, 36, 37]:

$$CR = 100 \times \left(1 - \frac{compressed\ size}{original\ size}\right) \tag{17}$$

Proposed method was evaluated on actual EMG data. We used two EMG signals baptized Kheir1 and Kheir2. The signals were amplified with a total gain of 2000, and sampled at 2048 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. Wavelet chosen for DWT is bi-orthogonal 4-4 [38]. Figures 4, 5, 6 and 7 show the obtained results.

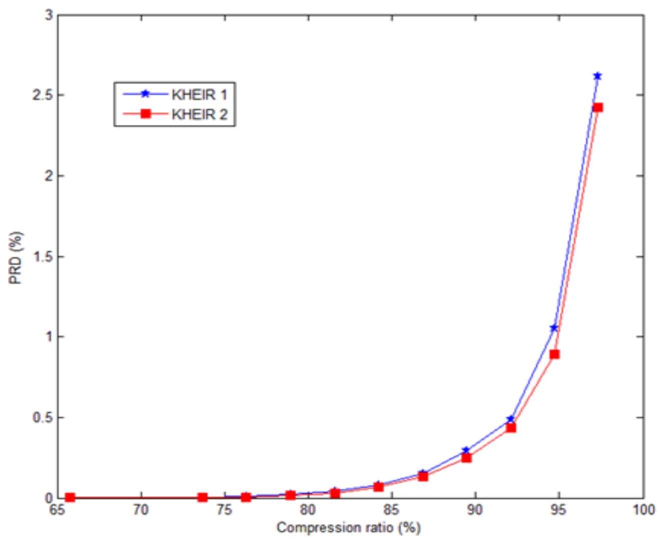

Figure 4. Compression ratio as a function of the PRD

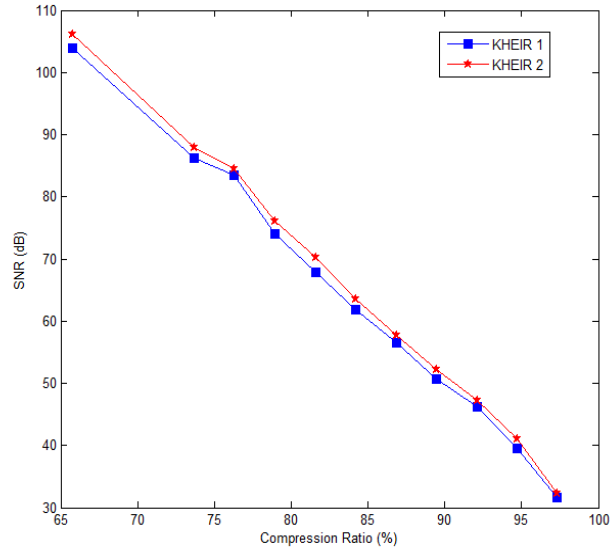

Figure 5. Compression ratio as a function of the SNR

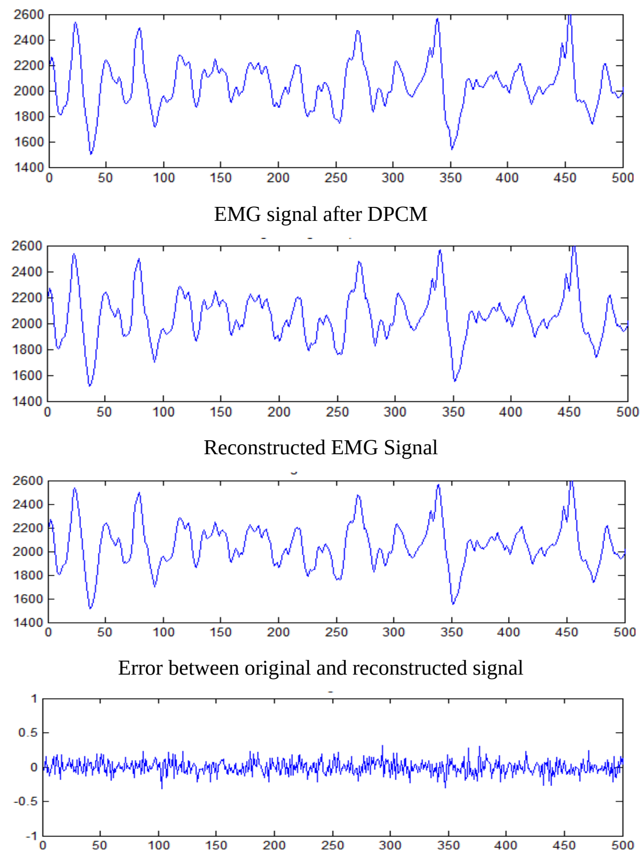

Figure 6. Reconstruction of EMG signal called Kheir1: CR = 73.68 %; PRD = 0.0048 %; SNR = 86.24dB; Rate = 10

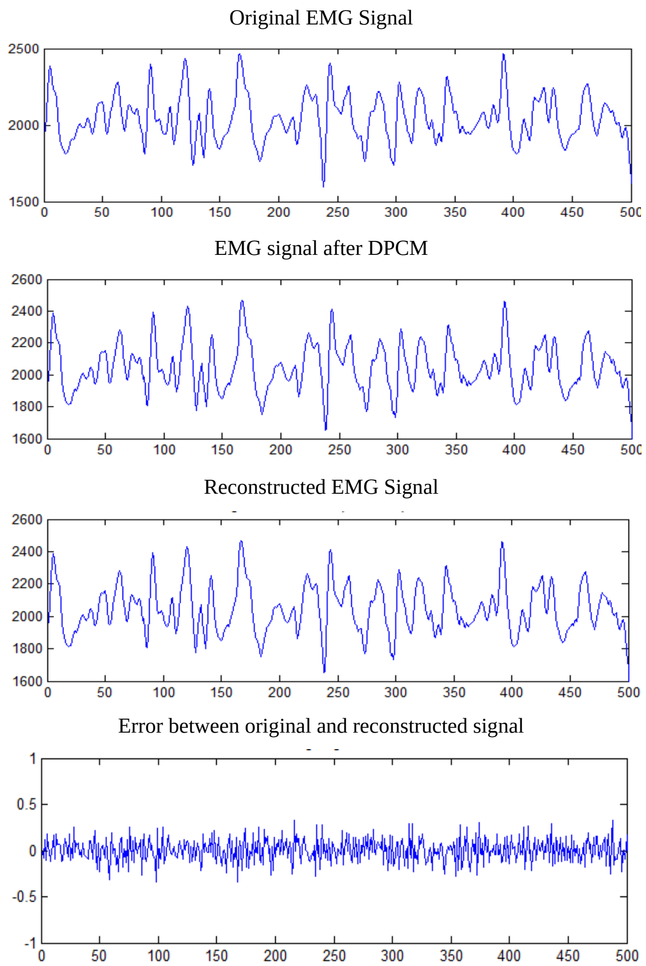

Figure 7. Reconstruction of EMG signal called Kheir2: CR = 73.68 %; PRD = 0.0040 %; SNR = 87.94dB; Rate = 10

Figures 4 and 5 shows variations of compression ratio as a function of SNR, and PRD for two EMG signals. According to these figures, it appears that PRD increases with compression ratio while SNR decreases. Reconstruction quality is good if the PRD is close to zero.

Table 1. Obtained results for kheir1

CR (%)	PRD (%)	SNR (dB)
97.3	2.6148	31.65
94.7	1.0523	39.56
92.10	0.4855	46.28
89.47	0.2913	50.71
86.84	0.1506	56.44
84.21	0.0815	61.78
81.57	0.0405	67.84
78.94	0.0199	74.01
76.31	0.0066	83.48
73.68	0.0048	86.24
65.78	0,0006	103.97

Based on the quality of reconstructed signals of figures 6 and 7, morphology of original signal is preserved. Tables 1 and 2 show the obtained results on EMG signals. These tables show the variation of Compression Ratio, PRD and SNR. From these tables, the CR is 97.30%, PRD to 0.0004 and SNR which continues to grow. Table 3 presents a comparison of results. This table shows that our algorithm has a slightly lower compression ratio compared to some of the works identified in the literature. A comparison of our results with those obtain before by Berger et al. [16], Norris et al. [15], Ntsama et al. [32], Marcus et al. [11] or Pedro et al. [39], shows a significant improvement of PRD. Introduction of the DPCM in compression chain strongly improves compression ratio.

Table 2. Obtained results for kheir2

CR (%)	PRD (%)	SNR (dB)
97.3	2.4214	32.32
94.7	0.8901	41.01
92.10	0.4342	47.25
89.47	0.2458	52.19
86.84	0.1291	57.78
84.21	0.0664	63.55
81.57	0.0304	70.32
78.94	0.0155	76.16
76.31	0.0059	84.54
73.68	0.0040	87.94
65.78	0.0004	106.10

Table 3. Comparison of the results

Method	PRD (%)	CR (%)
Proposed method	0.0048	73.68
Norris et al.[15]	3.8	75
Berger et al.[16]	2.5	75
Ntsama et al. [31]	0.01	61
Marcus et al. [11]	3.50	75
Pedro et al. [38]	1.4 à7.5	50 à90

5. Conclusions

In this paper, we have shown that it is possible to optimize and improve compression performance of an EMG signal by using the DPCM as preprocessing. The PRD can be improved.

However, it is very difficult to find the optimal size of the DPCM dictionary for efficient signal processing, without damaging it. The signal to noise ratio continues to grow (for PRD = 0.0004%, SNR = 106.1 dB). For compression ratio 81.57, reconstructed signal begins to degrade. We intend to extend this approach to other electrophysiological signals and improve this method by a significant reduction in SNR.

The research of optimal size of the codebook of DPCM will undoubtedly remain a prospect.

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