# On EMG Signal Compression with Recurrent Patterns

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***Abstract*—In this work the Multidimensional Multiscale Parser (MMP) is employed for encoding Electromyographic (EMG) signals. The experiments were carried out with real signals acquired in laboratory and show that the proposed scheme is effective, outperforming even wavelet-based state-of-the-art schemes present in the literature in terms of PRD $\times$ Compression Ratio.**

***Index Terms*—Electromyogram, Data Compression, Isometric Contractions.**

## I. INTRODUCTION

THE Electromyogram (EMG) is the electrical signal representing the contraction of muscles in human body. It can be acquired in basically two ways: with surface electrodes or needle electrodes [1]. The signals acquired with surface electrodes, the main focus of this work, are similar to noise, while signals from needle electrodes present some periodicity, as the one in electrocardiogram (ECG) records.

The raw surface EMG signal presents a noise-like appearance, because it is composed by a superposition of signals from many groups of muscle fibers near the sensor. Therefore, there is great interest in applying a suitable decomposition to it [2], [3], that is able to identify the action potentials produced by each group. This kind of processing, for instance, can be carried out in the study of muscular phenomena or in the development of motion support systems [5].

As the telemedicine advances, the need for EMG transmission increases. Besides, EMG storage is also important, which enables behavior comparison and disorder development analysis and diagnosis (dystrophy, peripheral nerve damage, weakness and etc.). This kind of signal presents bandwidths up to 600 Hz and it may be necessary to analyze several channels, during long periods [6]. These situations claim for a good compression method, which is able to represent these signals in a compact form while preserving all clinical information.

In this work we report the results of compressing raw surface EMG signals by using the Multiscale Multidimensional Parser (MMP) algorithm. In [7], the use of MMP for encoding multidimensional data was justified by its performance with Gaussian vectors. It is known that EMG signals present near Gaussian behavior [8], depending on the level of Maximum Voluntary Compression (MVC). Therefore, it is reasonable to use MMP for compressing EMG data. Our simulation results show that MMP performs well, overcoming state-of-the-art encoders present in literature, even wavelet-based ones.

This paper is organized as follows. In section II, the basic MMP-based framework for compressing EMG signals is presented. In section III, some basic aspects about EMG signals are discussed, as well as a justification for using MMP in their compression. Next, in section IV, we report experimental results and comparisons to state-of-the-art encoders. Finally, in section V we present our conclusions.

## II. THE MMP ENCODER

The Multidimensional Multiscale Parser (MMP) algorithm [7], [9] is a universal lossy compression method built upon the *multiscale recurrent pattern matching* concept. In it, two vectors $\mathbf{u}$ and $\mathbf{v}$ with different lengths $(\ell(u) \neq \ell(v))$ can be matched. This is possible through the use of a *scale transformation* $T^N(\mathbf{x}) : \mathbb{R}^{\ell(\mathbf{x})} \mapsto \mathbb{R}^N$ [7], [9], which is implemented with classical sampling-rate change operations.

The MMP has dictionaries $\mathcal{D}^{s_k} = \left\{\mathbf{v}_0^{s_k}, \mathbf{v}_1^{s_k}, \ldots, \mathbf{v}_{m-1}^{s_k}\right\}$ with $m$ vectors $\mathbf{v}_i$ at scale $k$, for $k = 0, 1, \ldots \log_2(N)$, which are used to encode segments of an input signal $\mathbf{X}^0 = \left( x(0) \quad x(1) \quad \ldots \quad x(N-1) \right)$, whose length $N$ is a power of 2. The dictionaries $\mathcal{D}^{s_k}$ together compose $\mathcal{D}$, the MMP's main dictionary. When attempting to encode the input segment $\mathbf{X}^0$, MMP searches in the dictionary $\mathcal{D}_R^{s_0}$, that is built from $\mathcal{D}^{s_0}$, for the best vector $\mathbf{v}_{i_0}^{s_0}$ to replace $\mathbf{X}^0$. If a suitable element is found, then the encoding of $\mathbf{X}^0$ is performed and MMP outputs a bit flag $'1'$, followed by the dictionary index $i_0$; otherwise, MMP splits the input segment into two other segments, $\mathbf{X}^1 = \left( x(0) \quad x(1) \quad \ldots \quad x(N/2-1) \right)$ and $\mathbf{X}^2 = \left( x(N/2) \quad x(N/2+1) \quad \ldots \quad x(N-1) \right)$, and outputs a bit flag $'0'$, repeating the encoding procedure for $\mathbf{X}^1$. After the encoding of $\mathbf{X}^1$ is done, the algorithm encodes $\mathbf{X}^2$ in the same way. The segmentation procedure is recursively repeated until a matching attempt is successful or the resulting segments have length $\ell(\mathbf{X}^j) = 1$.

The segmentation of the input segment $\mathbf{X}^0$ is represented by means of a segmentation tree $\mathcal{S}$. Each node $n_j$ of $\mathcal{S}$ is associated to a segment $\mathbf{X}^j$ of the input segment, of length $2^{-p}N$, where $p$ is the depth of the node $n_j$ in the segmentation tree $\mathcal{S}$.

The choice of the best segment is based on the minimization of the *Lagrangian* cost $J(n_j)$, defined as:

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$$D(n_j) = d\left(\mathbf{X}^j, \mathbf{v}_{i_j}^{s_k}\right) \quad (1)$$

$$R(n_j) = -\log_2\left(\Pr\left\{\mathbf{v}_{i_j}^{s_k}\right\}\right) \quad (2)$$

$$J(n_j) = D(n_j) + \lambda R(n_j) \quad (3)$$

where $\mathbf{v}_{i_j}^{s_k}$ is the vector $\mathbf{v}_{i_j}$ at scale $k$, $d(\mathbf{u}, \mathbf{v})$ is some distortion metric (usually the squared error) and $\Pr\left\{\mathbf{v}_{i_j}^{s_k}\right\}$ is the probability of the vector of index $i_j$, at scale $k$, being chosen for encoding a given signal segment. The Lagrangian cost of the segmentation tree $\mathcal{S}$ is defined as $J(\mathcal{S}) = D(\mathcal{S}) + \lambda R(\mathcal{S})$, where $D(\mathcal{S})$ is the distortion obtained when using $\mathcal{S}$, $R(\mathcal{S})$ is the rate (flags and indices), and $\lambda$ is the Lagrangian multiplier, which controls the trade-off between distortion and rate. High $\lambda$'s result in high compression with high distortion, and small values result in low compression with low distortion.

The segmentation tree $\mathcal{S}$ is optimized in a rate-distortion sense. The basic optimization procedure begins with a full segmentation tree and continues from the leaf nodes to the root, pruning the children nodes $n_{2j+1}$ and $n_{2j+2}$ whenever the Lagrangian cost [7], [9] of the tree containing them is greater than the cost of the segmentation tree without $n_{2j+1}$ and $n_{2j+2}$. After this first step, an analysis is carried out to verify if any two neighbor nodes not sharing the same parent node can be joined together (encoded as only one dictionary index) to lower the Lagrangian cost [9].

The representation $\hat{\mathbf{X}}^0$ created by MMP generally presents severe discontinuities at the boundaries of the segments $\hat{\mathbf{X}}^j$ generated by the segmentation procedure, even if the original input vector $\mathbf{X}^0$ is smooth. The cause for this behavior lies on the fact that input segments are encoded independently of the representations chosen for its neighbors.

This problem can be circumvented by creating a dictionary that takes into account the previous choices made by the algorithm. In this way, the dictionary $\mathcal{D}_R^{s_k}$ is built by choosing the $N_R$ vectors $\mathbf{v}_i^{s_k} \in \mathcal{D}^{s_k}$ that best match the causal neighborhood, that is, the previously encoded segments to the left of the current one. Given that the position of $\mathbf{X}^j$ inside $\mathbf{X}^0$ is given by

$$Fp(j) = N\left((j+1)\,2^{-\lfloor \log_2(j+1)\rfloor} - 1\right), \quad (4)$$

where $N$ is the length of $\mathbf{X}^0$, the length $N^j$ of $\mathbf{X}^j$ can be evaluated as $N^j = N 2^{-\lfloor \log_2(j+1), \rfloor}$ and the *left neighbor* of $\mathbf{X}^j$ is given by

$$\mathbf{L}^j = \left(\ \hat{x}(Fp(j) - N^j) \quad \ldots \quad \hat{x}(Fp(j)-1)\ \right),\ Fp(j) \geq 1. \quad (5)$$

The similarity with the causal neighborhood is measured using the *rugosity* metric [9], defined as

$$R(\mathbf{v}_i^{s_k}, j) = \Big| \left|L^j(N^j-3) - L^j(N^j-1) + v_i^{s_k}(0) - v_i^{s_k}(2)\right| - \left\lfloor \frac{4}{3}\left|L^j(N^j-2) - v_i^{s_k}(1)\right| \right\rfloor \Big|. \quad (6)$$

Following this concept, MMP always encodes $\mathbf{X}^j$ with the dictionary $\mathcal{D}_R^{s_k}$, which contains the $N_R$ "least rugose" vectors from $\mathcal{D}^{s_k}$ according to (6).

The encoding process starts with a very simple initial dictionary, composed by the $1 \times 1$ elements with amplitudes $\{0, 4, 8..., 2^M - 1\}$; when expanded to the other scales, they generate dictionaries having only constant elements. One of the advantages of MMP is that its dictionary can be updated as encoding proceeds. The main dictionary ($\mathcal{D}$) is updated as follows: whenever the reconstructed segments $\hat{\mathbf{X}}^{2j+1}$ and $\hat{\mathbf{X}}^{2j+2}$ associated to the children nodes $n_{2j+1}$ and $n_{2j+2}$ are available, MMP concatenates them and generates $\hat{\mathbf{X}}^j$ as the reconstructed segment associated to the parent node $n_j$, including it in every dictionary $\mathcal{D}^{s_k}$ using the scale transformations [7], [9].

As shown in the last paragraph, any element in the dictionary has an origin scale, from which it is transformed. Then, it is possible to separate its representation into two components: *origin scale* and *index*. This way, each dictionary $\mathcal{D}^{s_k}$ can be divided into $1 + \log_2(N)$ sub-dictionaries, one for each origin scale. The rate needed to specify the element $\mathbf{v}_{i_j}^{s_k}$ was given by eq. (2). The new approach turns it into

$$R(n_j) = -\left(\log_2(\Pr(\mathcal{D}^{s_k,s_l})) + \log_2(\Pr(\mathbf{v}_{i_j}^{s_k,s_l}))\right), \quad (7)$$

where $\Pr(\mathcal{D}^{s_k,s_l})$ is the probability that the element chosen for encoding $\mathbf{X}^j$, at scale $k$, belongs to the sub-dictionary with elements transformed from scale $l$ and $\Pr(\mathbf{v}_{i_j}^{s_k,s_l})$ is the probability of element $\mathbf{v}_{i_j}^{s_k,s_l}$, located in position $j$ of the sub-dictionary at scale $k$ with elements transformed from scale $l$, being chosen for encoding a given signal block. So, we can also use an adaptive arithmetic encoder to reduce the rate needed to specify $\Pr(\mathcal{D}^{s_k,s_l})$, as already done for elements $\mathbf{v}_{i_j}^{s_k,s_l}$.

To improve the exploitation of redundancies among signal segments, a *displacement dictionary* $\mathcal{D}_D$ [9] is also used when encoding a segment $\mathbf{X}^j$, which contains displaced versions of the approximations for previously encoded segments. This dictionary is implemented by keeping the $M$ last samples of the reconstructed signal. When building $\mathcal{D}_R^{s_k}$, elements from $\mathcal{D}^{s_k}$ as well as $\mathcal{D}_D^{s_k}$ are evaluated.

For more detailed information on the specific algorithm used here, the reader is referred to [9].

## III. The EMG signal

The muscles are composed of slender fibers organized in groups, which are called motor units [4]. These fibers are innervated by a single motoneuron, making them act together during muscular contractions. The motor unit is activated by electrical impulses along the motoneuron, sent by the nervous system. When these impulses come at a fast enough rate, a steady force is produced. Each nerve impulse induces an electrical discharge in each muscle fiber that it innervates, which spreads along them and produces an electrical potential. The EMG is the composition of the discharges from all motor units that the electrode can detect and represents the electrical activity of muscles during contractions [4].

The EMG can be used for detecting abnormal muscle electrical activity due to many disorders, like muscular dystrophy, inflammation or weakness, myasthenia gravis, peripheral nerve damage and disc herniation, among others. There are two types of EMG: intramuscular and surface. The former is carried out with needle electrodes inserted through skin, into the muscle, and the latter involves placing electrodes on the skin just above the muscle, being a non invasive approach. Although intramuscular EMG has been widely used in the past due to the good quality of the signal obtained on the electrodes, the interest in surface EMG has been increasing a great deal in the last few years. This is so because, with this approach, there is no skin damage, which makes it very valuable in monitoring the progression of disorders of nerves and muscles.

The waveform on the surface electrodes presents a noise-like appearance. Indeed, its is known that the EMG recorded during constant force, constant angle, non-fatiguing contractions can be modeled as a zero mean, correlation ergodic, stochastic process with Gaussian distribution, depending on the level of MVC ( $>$ 30%) [8]. This is a very important feature because it may help to tune the encoder and allows early assumptions about the input signal.

The MMP is a universal encoder. In addition, it was shown in [7] that MMP can present good performance when compressing Gaussian vectors, given the multiscale pattern matching approach. Therefore, this universality together with the suitability to encode Gaussian signals make it a good candidate for EMG signal compression. In the next section, we show simulation results of EMG compression using MMP.

## IV. Experimental results

The efficiency of the proposed framework was addressed by running tests with EMG signals collected from the *biceps brachii* of $13$ subjects with pre-amplified electrodes, during isometric contractions, while they were seated with the upper-arm parallel to the torso and sustaining 60% of the MVC. Then, the resulting EMG's were sampled at $2000$ Hz and quantized with $12$ bits. The duration of the signals range from $1.3$ to $3.0$ minutes. Each input signal was then split into segments of $64$ samples, which were sequentially processed by the algorithm. It is worth noticing that, given the sustained MVC, the output signal presents a near-Gaussian behavior. The quality of the reconstructed signals was evaluated by using the percent root mean square difference (PRD), commonly adopted in the literature, defined as

$$PRD = \sqrt{\frac{\sum_{i=0}^{N-1}(x(i)-\hat{x}(i))^2}{\sum_{i=0}^{N-1}(x(i)-\mu)^2}} \times 100\%, \quad (8)$$

where $x(n)$ and $\hat{x}(n)$ are the original and the reconstructed signals, respectively, $N$ is their length and $\mu$ is the baseline value of the analog-to-digital conversion used for the acquisition of the data $x(n)$ ($\mu = 0$ for the test EMG signals). The compression factor (CF) is evaluated as

$$CF = \frac{B_o - B_c}{B_o} \times 100\%, \quad (9)$$

where $B_o$ is the total number of bits in the original signal and $B_c$ is the total number of bits in the compressed format, including header information. For each of the test signals, $B_o = 12 \times n$, corresponding to the $12$ bits resolution and the $n$ samples present in each record. The results are summarized in Fig. 1. The MMP algorithm was run for each of the 13 isometric EMG signals, leading to compression factors ranging from 50% to 95%. Fig. 1(a) shows CF $\times$ PRD curves for all signals, together with an average curve. We also provide a comparison to the algorithms in [6] and [10] in Fig. 1(b). The former is based on wavelets and a dynamic bit-allocation scheme, which uses a Kohonen layer (an artificial neural network). The latter is an EZW-based one, which proved to be superior to other schemes based on standard wavelets. Note that the results in [6] and [10] are state-of-the-art – Guerrero et. al [1] showed that transform-based compression methods tend to give good results, the best being given by wavelet-based ones. The signals used in the present work are very similar the ones used in [6], where a comparison to the results in [10] is made. Actually, the authors of [6] kindly provided these test signals. The proposed algorithm outperformed both methods for isometric-contraction signals. Although the other tested methods tend to cluster at high compression factors, the proposed method is markedly superior for the same range. At CF's below $84$%, the proposed method keeps a reasonable PRD, which is in general enough for not compromising the diagnosis, as needed in biological signal compression.

The proposed method can also be compared to the one in [11], in which EMG signals were quantized with 12 bits and sampled at 2048 Hz. However, the recorded signals were off-line band-pass filtered in the range $10$-$400$ Hz and downsampled to $1024$ Hz before compression. Although we use a sampling rate of 2000 Hz and higher bandwidths, a rough comparison is possible. In [11] the authors report a PRD of $5.95$% for a CF of $87.3$% and a MVC of 50% and a PRD of $5.26$% for a CF of $87.3$% and a MVC of 70%, which gives an average of $5.60$%. The proposed approach results in a PRD of $5.30$% for the same conditions. This is an indication that the proposed algorithm is comparable to the one in [11]. We have also run tests to verify if the proposed method preserves the main spectral features of EMG signals, represented by the mean frequency, the median frequency, the variance and the skewness, in the same way as done in [11]. When performing calculations, we noticed that some records presented odd values, completely different from the original ones. A closer analysis of the signal showed that there is only noise at the beggining and at the end of these records, with small amplitude. This results in zero reconstructed values and consequently zero periodogram outputs. This kind of behavior compromises the calculation of the spectral features, as we could verify. Given that, the beginning and the final part of some records were not considered during calculation. The relative change (percent variation) in these variables, for a CF of approximately $87.3$%, was $1.6201 \pm 1.1184$ for the mean frequency, $0.9849 \pm 1.2462$ for the median frequency, $9.1189 \pm 5.9106$ for the variance, and $56.2935 \pm 21.3781$ for the skewness (presented in the form *mean percentage* $\pm$ *deviation*). The results for the mean and median frequencies are below 10% and are comparable to the ones in [11]; however, the moments are not well preserved and present large variation. A reason for this behavior is that the MMP algorithm works on the time domain, and uses the mean squared error as the distortion metric; this favours the maintenance of the shape (as can be seen from the good PRD results), but not the spectral features. One possible solution for it, that is a promising area for future work, is to add other distortion metrics to equation 1, taking into account spectral features.

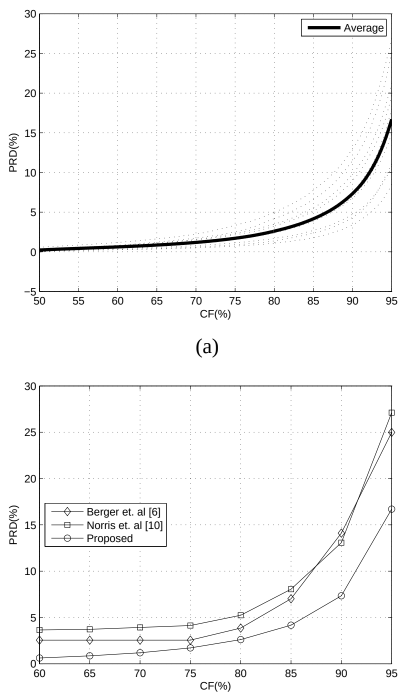


Fig. 1. Simulation results: Percent Root Mean Square Difference (PRD) *versus* Compression Factor (CF). a) Performance for the 13 isometric-contraction test signals. b) Comparison to wavelet-based algorithms.

Another promising research direction would be to use the proposed algorithm to compress isotonic signals. Since it uses an adaptive dictionary, it has the potential to capture and quickly adapt to the non-stationary characteristics presented by such signals.

The computational complexity of the MMP algorithm is reasonably high and a simplified analysis concerning this matter is available in [9]. Besides, we have not developed fast algorithms for its implementation yet, since currently the main goal is to identify its potentials and investigate enhancements for improving its performance for a variety of signals, like EMG. Given these observations, we did not carried out complexity comparisons in the context of this paper, however, this is a main concern for future works.

## V. Conclusions

We applied a one-dimensional version of the MMP algorithm to the compression of EMG data. The base algorithm and its extensions, composed by tools that allow better adaptation to smooth sources and more effective use of the dictionary, provided reconstructed signals with high quality. The results obtained for isometric signals were good, outperforming state-of-the-art schemes for EMG compression in terms of PRD $\times$ Compression Ratio. In brief, this work enforces that the MMP algorithm, due to its universality, is an interesting alternative for biological signal encoding, and can be a viable alternative to compressing other data of the same class, like Electroencephalograms (EEG).

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## References

[1] A. P. Guerrero and C. Mailhes, "On The Choice Of An Electromyogram Data Compression Method," *Proceedings of the 19th International Conference - IEEE/EMBS*, Chicago, Illinois, November 1997.

[2] E. Plevin and D. Zazula, "Decomposition of Surface EMG Signals Using Non-Linear LMS Optimisation of Higher-Order Cumulants," *15th IEEE Symposium on Computer-Based Medical Systems*, p. 49, June 2002.

[3] D. Farina, R. Merletti, R. M. Enoka, "The extraction of neural strategies from the surface EMG," *Journal of Applied Physiology*, Vol. 96, No. 4, pp. 1486-1495, April 2004.

[4] M. Nikolic, "Detailed Analysis of Clinical Electromyography Signals EMG Decomposition: Findings and Firing Pattern Analysis in Controls and Patients with Myopathy and Amytrophic Lateral Sclerosis," *PhD Thesis*, Faculty of Health Science, University of Copenhagen, 2001.

[5] T. Hoshino, M. Tomono, R. Furusawa, T. Suzuki, M. Shimojo, and K. Mabuchi, "Development of a Motion Support System by Using an Electromyogram," *Proceedings of the IEEE International Conference on Systems, Man and Cybernetics*, Vol. 5, pp. 4432-4437, The Hague, The Netherlands, October 2004.

[6] P. A. Berger, F. A. O. Nascimento, J. C. Carmo, and A. F. Rocha, "Compression of EMG signals with wavelet transform and artificial neural networks," *Institute of Physics Publishing: Physiological Measurement*, Vol. 27, No. 6, pp. 457-465, June 2006.

[7] M. B. de Carvalho, E. A. B. da Silva, and W. A. Finamore, "Multidimensional signal compression using multiscale recurrent patterns," *Signal Processing: Image and Video Coding beyond Standards*, Vol. 82, No. 11, pp. 1559-1580, November 2002.

[8] K. Nazarpour, A. R. Sharafat, and S. M. Firoozabadi, "Negentropy Analysis of Surface Electromyogram Signal," *Proceedings of the 13th IEEE Workshop on Statistical Signal Processing*, pp. 974-977, Bordeaux, France, July 2005.

[9] E. B. L. Filho, E. A. B. da Silva, M. B. Carvalho, W. S. S. Júnior and J. Koiller, "Electrocardiographic Signal Compression using Multiscale Recurrent Patterns", *IEEE Transactions on Circuits and Systems–I: Regular Papers*, Vol. 52, No. 12, pp. 2739-2753, December 2005.

[10] J. A. Norris, K. Englehart, and D. Lovely,"Steady-state and dynamic myoelectric signal compression using embedded zero-tree wavelets," *Proceedings of the 23rd Annual EMBS International Conference*, pp. 1879-1882, October 2001.

[11] E. Carotti, J. C. De Martin, R. Merletti, and D. Farina, "Compression of surface EMG signals with algebraic code excited linear prediction," *Medical Engineering & Physics*, Vol. 29, No. 2, pp. 253-258, May 2006.