LINEAR PREDICTIVE CODING OF MYOELECTRIC SIGNALS

Elias S. G. Carotti[1], *Juan Carlos De Martin*[2], *Dario Farina*[3], *Roberto Merletti*[3]

[1] Dipartimento di Automatica e Informatica/[2]IEIIT-CNR/[3]Dipartimento di Elettronica
Politecnico di Torino
Corso Duca degli Abruzzi, 24 — I-10129 Torino, Italy
E-mail: [carotti|demartin|farina|merletti]@polito.it
Phone: ++39-011-564-[5421|7036] (Fax: -7099)

ABSTRACT

Despite the great interest towards long term recordings of Electromyographic (EMG) signals, which find applications for example in telemedicine, only a few studies have dealt with compression of these signals. In this paper we propose a lossy coding technique for surface EMG signals. The technique is based on the Linear Predictive Coding paradigm widely used for speech compression. The algorithm was tested on both simulated and experimental signals. Mean frequency, median frequency, variance, skewness, and kurtosis of the EMG signals were preserved with an error less than 3% with respect to the original values for synthetic signals and experimental signals, reducing the bitrate from 24 kbit/s (12 kbit/s after downsampling) to 352 bit/s, with a compression factor of 97.1%. It was concluded that the Linear Predictive Coding paradigm can be effectively used for high rate compression of surface EMG signals when preservation of only the power spectrum of the signal is of interest. This has applications in ergonomics and occupational medicine.

1. INTRODUCTION

Recordings of electromyographic (EMG) signals can have a duration of hours when muscle function is to be continuously monitored [1]. As an example, surface EMG signals are acquired during working activities in occupational medicine for detecting muscle overload which may determine work-related musculo-skeletal disorders. Compression of these large amount of data is necessary in most cases, such as when EMG data are acquired on a patient and sent remotely to be processed and analyzed (telemedicine). Surface EMG signals are usually acquired at 12–16 bit/sample, at sampling rates ranging from 1 kHz to 10 kHz. Moreover, many detection systems are often applied on the same subject, leading to multi-channel recordings.

Extensive work on signal compression has been done in related fields, such as electrocardiogram (ECG) [2] or electroencephalogram (EEG) signal coding [3]. However, despite the importance of the possible applications, there are still few works dealing with EMG signals.

Norris *et al.* [4], one of the pioneers in this research area, investigated lossy compression of EMG signals using adaptive differential pulse code modulation (ADPCM), a technique commonly applied to speech signals. Guerrero *et al.* [5] compared the performance of common compression techniques, mostly adopted for speech signal coding, applied to EMG signals. More recently, the use of wavelets has been suggested for EMG signal compression [6]; EZW, the wavelet-based algorithm used in JPEG2000 for coding still images, was also applied to EMG signals [7].

These techniques were designed to preserve, with various degrees of accuracy, the waveform of the encoded signal, although for some applications a reconstruction of the waveform may not be needed, while it is important to preserve the signal spectrum only. It may indeed be of importance to monitor spectral changes occurring slowly over time due to continuous muscle activation, as occurs in monitoring muscle activity during repetitive work activities at low contraction levels (e.g., computer work) [8]. EMG signals presenting continuous activity may be considered WSS over short time windows (0.5-1 s). The spectrum of these EMG signals can be successfully described with an autoregressive (AR) model [9][10].

In this paper we propose a novel compression technique which preserves EMG spectral features. The method is based on a model approach, laying its foundation in the Linear Predictive Coding and the related Autoregressive Modeling theory.

The rest of this paper is organized as follows: in section 2 the coding requirements are described; the proposed solution is presented in section 3; the signals used as a test set for the proposed algorithm are described in section 4 and in section 5 results are discussed; finally conclusions are drawn in section 6.

2. SURFACE EMG VARIABLES

The features of surface EMG that we decided to preserve after compression are: the mean and median frequency, variance, skewness and kurtosis of the estimated power spectral density [11]. The moments of the PSD $P[f]$ in the positive frequency domain are defined as follows:

$$M_k = \sum_{i=1}^{N} f_i^k P[f_i] \cdot (f_i - f_{i-1}) \quad (1)$$

$$M_{Ck} = \sum_{i=1}^{N} (f_i - M_1)^k P[f_i] \cdot (f_i - f_{i-1}), \quad (2)$$

where M_k and M_{Ck} are the standard and central moments of order k.

Mean frequency f_{mean} is defined as

$$f_{\text{mean}} = \frac{\sum_{i=1}^{+N} f_i P[f_i] \cdot (f_i - f_{i-1})}{\sum_{i=1}^{+N} P[f_i] \cdot (f_i - f_{i-1})}, \quad (3)$$

where N is the number of frequencies for which the PSD has been estimated.

Median frequency f_{med} is the frequency such that half of the power of the signal is due to harmonics at frequencies lower than f_{med}, i.e.:

$$\sum_{i=1}^{f_{\text{med}}} P[f_i] \cdot (f_i - f_{i-1}) = \sum_{i=f_{\text{med}}}^{+N} P[f_i] \cdot (f_i - f_{i-1}) = \frac{1}{2} \cdot \sum_{i=1}^{+N} P[f_i] \cdot (f_i - f_{i-1}). \quad (4)$$

Under certain conditions, a variation in f_{med} and f_{mean} provides an indication on the change in muscle fiber conduction velocity [11].

The second-order central moment, M_{C2}, i.e., the variance of the PSD, is computed as

$$M_{C2} = M_2 - M_1^2 = \sum_{i=1}^{+N} (f_i - f_{\text{mean}})^2 P[f_i] \cdot (f_i - f_{i-1}). \quad (5)$$

The normalized third central moment, i.e., the *skewness*, μ_3, is defined as:

$$\mu_3 = \frac{M_{C3}}{M_{C2}^{3/2}} = \frac{\sum_{i=1}^{+N} (f_i - f_{\text{mean}})^3 P[f_i] \cdot (f_i - f_{i-1})}{(\sum_{i=1}^{+N} (f_i - f_{\text{mean}})^2 P[f_i] \cdot (f_i - f_{i-1}))^{3/2}}. \quad (6)$$

Skewness bears information on the asymmetry of the PSD with respect to the mean frequency.

The normalized form of the fourth order central moment, the *kurtosis*, μ_4, expresses the degree of peakedness of the PSD, and is defined as:

$$\mu_4 = \frac{M_{C4}}{M_{C2}^2} = \frac{\sum_{i=1}^{+N} (f_i - f_{\text{mean}})^4 P[f_i] \cdot (f_i - f_{i-1})}{(\sum_{i=1}^{+N} (f_i - f_{\text{mean}})^2 P[f_i] \cdot (f_i - f_{i-1}))^2}. \quad (7)$$

3. ALGORITHM DESCRIPTION

The surface EMG signals were divided in time epochs of 1 s. A parametric model-based approach was applied to preserve the spectral envelope irrespective of the signal waveform; thus, the mean square error of the reconstruction with respect to the original signal can not be used as performance metric.

The first step was downsampling the signals to 1 kHz, since all the relevant information is contained in the first 512 Hz; then a four-tap high-pass filter, with cutoff frequency 10 Hz, was applied to the signals to remove the significant DC component. The downsampling operation brought the bitrate from 24 kbit/s down to 12 kbit/s (each sample is 12 bit wide).

The EMG signals were then divided into a number of frames which were independently processed and coded. Each frame was modeled with an all-pole filter driven with unit-variance gaussian white noise, according to the AR model theory:

$$H(z) = \frac{b_0}{1 + \sum_{n=1}^{p} a_n z^{-n}}, \quad (8)$$

where p represents the model order and the coefficients a_n can be also viewed as the optimal linear predictor coefficients in a Linear Predictive Coding (LPC) paradigm.

The coefficients a_n were computed using the autocorrelation method, which is guaranteed to assure the stability of the filter. Stability is especially important if a realization of the signal is needed at the decoder, even though, as a side effect of our modeling technique, information about the phase of the signal is lost, because Eq. (8) generates a model which is minimum phase. The direct consequence is that the waveform of the signal is generally not preserved; anyway this was not an issue for our purposes, since we just needed to accurately represent the spectrum of the signal.

The "goodness" of the model strongly depends on its order p, which should be accurately chosen because a model order too low does not preserve with enough accuracy the spectrum, especially for what concerns the higher order moments, while if p is too high the model is overfit; moreover the final bitrate grows linearly with p, as more coefficients have to be sent to the decoder.

The coefficients of the AR(p) model were sent to the decoder along with the energy of the signal, to have a sufficiently faithful reconstruction of the spectrum of $s(n)$. To further lower the bitrate, quantization could be considered.

Force level	f_{mean}		f_{med}		M_{C2}		μ_3		μ_4	
% of MVC	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
5	0.08	0.04	1.74	0.18	0.60	0.22	2.08	0.29	0.60	0.14
10	0.06	0.05	1.46	0.57	0.56	0.15	2.00	0.24	0.74	0.21
15	0.04	0.05	1.36	0.30	0.42	0.04	1.86	0.18	0.60	0.16
20	0.02	0.04	1.24	0.46	0.44	0.05	1.82	0.19	0.60	0.14
30	0.04	0.05	1.30	0.33	0.48	0.08	1.76	0.18	0.70	0.16
45	0.00	0.00	1.50	0.41	0.50	0.10	1.84	0.11	0.76	0.05
60	0.00	0.00	1.76	0.29	0.42	0.11	1.88	0.28	0.72	0.18

Table 1. Mean and standard deviation of the relative error (percentage of the original value) of the relevant parameters of the reconstruction with respect to the original synthetic signals. The signals were modeled as AR(10). The force level is expressed as a percentage of the maximal voluntary force (MVC).

Force level	f_{mean}		f_{med}		M_{C2}		μ_3		μ_4	
% of MVC	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
10	0.35	0.14	3.22	0.74	1.30	0.44	2.13	0.74	1.40	0.52
30	0.43	0.15	3.02	0.42	2.97	1.07	5.72	2.16	5.45	2.36
50	0.47	0.10	2.65	0.29	3.52	1.56	7.18	2.36	6.85	3.61
70	0.62	0.21	3.33	1.14	4.60	2.24	8.95	3.39	10.28	6.04

Table 2. Mean and standard deviation of the relative error (percentage of the original value) of the relevant parameters of the reconstruction with respect to the original experimental signal. The signals considered were recorded from 6 patients. The signals were modeled as AR(10). The force level is expressed as a percentage of the maximal voluntary force (MVC).

Direct quantization of the a_n coefficients is generally not advisable; the Line Spectral Pairs (LSF), an alternative representation of the a_n, could instead be profitably used to ensure maximum performance in terms of compression, quantized filter stability and interpolation efficiency.

4. TEST SIGNALS

The proposed compression algorithm has been tested on both simulated and experimental surface EMG signals.

4.1. Simulated EMG signals

Surface EMG signals were simulated with the model described in [12]. This model simulates synthetic motor unit action potentials generated by finite length fibers and detected by surface electrodes. The volume conductor (i.e., the tissues separating the muscle fibers and the recording electrodes) comprises the muscle, fat and skin tissues, separated by planar layers. The physical parameters of the model were selected as in [12]. Signals were generated as detected from the biceps brachii muscle at contraction forces from 5% to 100% of the maximal force.

4.2. Experimental EMG signals

Experimental EMG signals were collected from the biceps brachii muscle of six male subjects at contraction forces from 10% to 70% of the maximal force. A bipolar EMG detection system (inter-electrode distance 10 mm) was used for signal detection. The signals were amplified (amplifier with -3 dB bandwidth: 10-500 Hz), fed into a 12-bit acquisition board, and sampled at 2048 samples/s. Signal duration was 15 s.

5. RESULTS

We developed a preliminary version of the proposed technique in Matlab, experimenting with the various parameters of the model and we found that a frame size N of 1024 samples (which, at a sampling frequency of 1024 Hz, corresponds to one epoch of 1 s) and 4-16 LPC coefficients determined optimal performance in terms of reconstruction error of the selected features. Most signals could be adequately modeled with only 6 coefficients, with errors in the higher order spectral moments always below 10%; more specifically, experiments showed that to faithfully preserve mean and median frequency a 4-taps filter is usually sufficient, while preserving skewness and kurtosis usually requires more coefficients. This means that, with 10 LPC coefficients and the gain, saved as 4-bytes floating point and no quantization, the compression factor of the encoded signal with respect to the downsampled original signal is approximately 1:35.

A commonly accepted measure of compression is defined as:

$$C = 100 \cdot \frac{L_{\text{orig}} - L_{\text{comp}}}{L_{\text{orig}}} \%, \tag{9}$$

where $L_{\text{orig}}, L_{\text{comp}}$ are, respectively, the original and the compressed file length; with the assumptions above regarding the model order, $C \approx\ 97.1\%$.

The spectral parameters can be computed analytically from the reconstruction filter in equation (8).

The simulated and experimental signals were encoded with an AR(10) model. Table 1 shows the performance of the algorithm when applied to the set of simulated EMG signals while Table 2 reports the results obtained on the experimental signals.

Some of the experimental signals required filters with more than 10 taps to maintain the distortion in higher-order spectral moments below 10%. Experiments showed that in those cases up to 16 taps (an AR(16) model) could be necessary, possibly suggesting the adoption of an analysis-by-synthesis approach, in which more taps are added until distortion is kept under a predefined threshold. Moreover, if the waveform is to be preserved, a so-called hybrid technique, as those commonly used for speech coding (e.g., CELP), could be adopted.

6. CONCLUSIONS

In this paper we presented a technique for lossy coding of EMG signals. The proposed algorithm is based on a simple LPC procedure, along the lines of many algorithms commonly employed for speech coding. Despite the simplicity of the technique, experiments proved that faithful reconstruction of relevant spectral parameters was obtained, while guaranteeing compression gains of about 97.1% with respect to the original downsampled uncoded signal.

Further development should take into consideration the correlation between signals in multi-channel surface EMG recordings.

7. REFERENCES

[1] P. J. Mork and R. H. Westgaard, "The association between nocturnal trapezius muscle activity and shoulder and neck pain," *European Journal of Applied Physiology*, vol. 92, no. 1–2, pp. 18–25, 2004.

[2] S. M. S. Jalaleddine, C. G. Hutchens, R. D. Strattan, and W. A. Coberly, "ECG data compression techniques - a unified approach," *IEEE Transactions on Biomedical Engineering*, vol. 37, no. 4, pp. 329–343, Apr. 1990.

[3] G. Antoniol and P. Tonella, "EEG data compression techniques," *IEEE Transactions on Biomedical Engineering*, vol. 44, no. 2, pp. 105–114, Feb. 1997.

[4] J. F. Norris and D. F. Lovely, "Real-time compression of myoelectric data utilising adaptive differential pulse code modulation," *Medical & Biological Engineering & Computing*, vol. 33, pp. 629–635, 1995.

[5] Alfonso Prieto Guerrero and Corinne Mailhes, "On the choice of an electromyogram data compression method," in *Engineering in Medicine and Biology society. Proceedings of the 19th Annual International Conference of the IEEE*, Chicago, IL USA, Nov. 1997, vol. 4, pp. 1558 – 1561.

[6] P. Wellig, Cheng Zhenlan, M. Semling, and G. S. Moschytz, "Electromyogram data compression using single-tree and modified zero-tree wavelet encoding," in *Engineering in Medicine and Biology Society. Proceedings of the 20th Annual International Conference of the IEEE*, Hong Kong, China, Oct. 1998, vol. 3, pp. 1303–1306.

[7] J. A. Norris, K. Englehart, and D. Lovely, "Steady-state and dynamic myoelectric signal compression using embedded zero-tree wavelets," in *Engineering in Medicine and Biology Society. 23rd Annual International Conference of the IEEE*, Oct. 2001, vol. 2, pp. 1879–1882.

[8] B. Visser, M. De Looze, M. De Graaff, and J. Van Dieen, "Effects of precision demands and mental pressure on muscle activation and hand forces in computer mouse tasks," *Ergonomics*, vol. 47, pp. 202–217, 2004.

[9] Omry Paiss and Gideon F. Inbar, "Autoregressive modeling of surface EMG and its spectrum with application to fatigue," *IEEE Transactions on Biomedical Engineering*, vol. 34, no. 10, Oct. 1987.

[10] Tohru Kiryu, Carlo J. De Luca, and Yoshiaki Saitoh, "AR modeling of myoelectric interference signals during a ramp contraction," *IEEE Transactions on Biomedical Engineering*, vol. 41, no. 11, pp. 1031–1038, Nov. 1994.

[11] Roberto Merletti, Archil Gulisashvili, and Loredana R. Lo Conte, "Estimation of shape characteristics of surface muscle signal spectra from time domain data," *IEEE Transactions on Biomedical Engineering*, vol. 42, no. 8, pp. 769–776, Aug. 1995.

[12] D. Farina and R. Merletti, "A novel approach for precise simulation of the emg signal detected by surface electrodes," *IEEE Transactions on Biomedical Engineering*, vol. 48, pp. 637–646, 2001.