MATRIX-BASED LINEAR PREDICTIVE COMPRESSION OF MULTI-CHANNEL SURFACE EMG SIGNALS

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ABSTRACT

We propose a linear predictive coding technique for multi-channel electromyographic (EMG) recordings. The signals are acquired using two-dimensional grid of electrodes which generate strongly correlated signals. Previous work only considered spectral redundancy across the signal matrix. In this paper we exploit the correlation present in the residual signals, i.e., the signals after the short term prediction. The proposed technique achieves a compression ratio of about $1 \div 9$, i.e., slightly better than spectral-only decorrelation methods, but with a strong increase of approximately 3.2 dB SNR in the quality of the reconstructed waveform.

***Index Terms*—** Data compression, Linear predictive coding, Electromyography

1. INTRODUCTION

Many diagnostic and monitoring activities require acquisitions of electromyographic (EMG) signals, that can last many hours, as when studying working activities [1].

Surface EMG signals are usually acquired at 12–16 bit/sample, at sampling rates ranging from 1 kHz to 10 kHz. Moreover, multi-channel surface EMG recordings are becoming increasingly important for clinical and research applications since they allow extraction of information concerning individual motor units, their peripheral and centrally controlled properties. The current technology allows the concomitant detection of hundreds of EMG signals from closely located positions over the skin, thus efficient compression techniques become crucial, particularly if the signals have to be sent to a remote location, e.g. to perform remote diagnosis.

In spite of the many useful applications, so far only few studies have dealt specifically with compression of single-channel surface EMG signals; even fewer were explicitly devoted to multi-channel surface EMG compression.

Norris *et al.* [2] pioneered lossy compression of single-channel EMG signals using adaptive differential pulse code modulation (ADPCM), a technique commonly applied to speech signals. Guerrero *et al.* [3] compared the performance of common speech compression techniques, applied to EMG signals. More recently, the use of the wavelet transforms has been suggested for single-channel EMG signal compression[4, 5]. In [6], AR modeling was followed by analysis-by-synthesis quantization of the residual signal to allow high-quality waveform reconstruction.

The EMG signals acquired from a muscle during a voluntary contraction exhibit high correlation across the matrix. Recently, a technique exploiting the strong correlation between the parameters of the AR models of adjacent EMG signals in a matrix was proposed [7], achieving higher compression than [6] while maintaining comparable performance in terms of the quality of the reconstructed waveform.

In this paper we present a surface EMG compression technique which extends the method proposed in [7], by exploiting the correlation between adjacent signals of EMG signal matrix recordings.

The rest of this paper is organized as follows: our previous multi-channel approach to EMG signal matrix compression [7] is briefly reviewed in Section 2, then the proposed technique is presented in Section 3; the signals used as a test set are described in Section 3, and the EMG features we wanted to preserve in Section 5; in Section 6 results are presented; finally conclusions are drawn in Section 7.

2. REVIEW OF MULTI-CHANNEL EMG SIGNALS CODING IN THE ACELP FRAMEWORK

In previous works [6][7], the widely used speech compression approach known as Algebraic Code Excited Linear Prediction (ACELP) was selected to compress EMG signals because it had been previously shown that EMG signals could be successfully represented using AR-modeling and quantization of the residual, despite the different nature from speech signals.

A typical ACELP coder computes the parameters of a tenth order AR model of the speech signal (sampled at 8 kHz, 12 bit/sample) and transmits the model parameters. The all-pole filter corresponding to the AR model captures the shape of the power spectrum of the signal or, in the time domain, the short term correlation among samples and is thus called Short Term Predictor (STP) filter. The longer term temporal correlation is removed by means of the Long Term Predictor (LTP) and the residual excitation quantized with the algebraic codebook.

Analogously, the single-channel surface EMG signal is divided into 160-sample frames without pre-processing; each frame is further divided into 40-sample subframes corresponding to 39.06 ms for a sampling frequency $f_s = 1$ kHz. The STP parameters are computed on these subframes, but because they are floating point values they are quantized for transmission. Since filter stability cannot be guaranteed if these coefficients are directly quantized, ACELP transforms these coefficients into Line Spectral Frequencies (LSF).

Multi-channel surface EMG signals are usually acquired using a rectangular array of sensors, each recording the signal due to a contraction of the muscle at a different spatial position. Fig. 1 depicts a few EMG signals belonging to the same multi-channel recording, collected along the muscle using a matrix of electrodes.

Because of the high correlation between signals in an EMG matrix recording, adjacent signals have very similar power spectra. This structure can be easily exploited by means of predictive vector quantization of the LSFs. Thus, in [7], LSF prediction was performed using a fixed predictor whose coefficients had been previously offline learned on a training set. The resulting LSF prediction error was then coarsely quantized with a vector quantizer and the corresponding quantization index sent to the decoder. The authors showed that for this purpose, 13 bits would suffice to attain similar performance as with 38-bit independent quantization of the LSFs as in [6]. Since prediction only relied on previously coded data, the decoder could perform the same computation and reconstruct the signal. Of course, signals at the border of the matrix were still coded independently as in [6], i.e., with regular ACELP.

After STP prediction the residual was searched for longer term redundancy by means of the LTP filter (on the assumption that longer term correlation may still be present like in the speech signals) independently for each signal and the residual quantized with the fixed algebraic codebook. For each 40-sample subframe, the codebook was searched for the 10 unitary pulses that minimize the mean square error of the reconstruction, and the corresponding index sent to the decoder along with the corresponding codebook gain.

3. COMPRESSION ALGORITHM

While in the case of speech and single-channel EMG signals the residual excitation signal after STP and LTP filters is generally supposed to be white, there is still significant correlation among adjacent signals as it can be assessed by estimating the cross-correlation functions. In particular, most signals exhibit stronger correlation in the direction longitudinal to the muscle fibers and lower but significant correlation in the transverse direction. Moreover, from preliminary tests (results not shown), it was observed that LTP did not substantially improve the quality of the reconstruction and was therefore omitted. The residual excitation signal are thus coded after the STP filter, without the LTP.

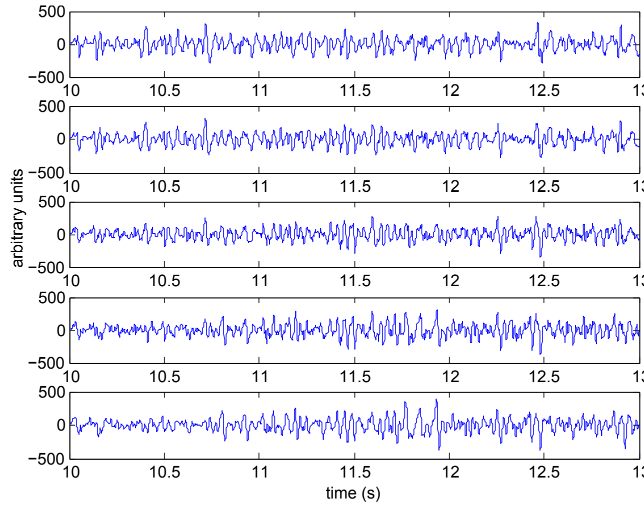

Fig. 1. EMG signals collected from different electrodes in a matrix along the muscle axis at the same time frame.

While signals at the border of the matrix are still coded independently and the residual just quantized with the algebraic codebook as it is, the excitation of the inner signals (i.e. all the signals excluding the first row and the first column) in an EMG signal matrix can be successfully predicted from the excitation of the adjacent signals.

Given the excitation of a generic single-channel signal at spatial position (i, j), $(i, j) \in [2, W] \times [2, H]$ in a $W \times H$ multi-channel EMG recording, $\underline{\mathrm{R}}_{(i,j)} = [r_{(i,j)}[0], r_{(i,j)}[1], \ldots, r_{(i,j)}[39]]$, a prediction can be formed as:

$$\hat{\mathrm{r}}_{(i,j)}(t) = \sum_{k=-\mathrm{T1}}^{\mathrm{T2}} \alpha_k \cdot \tilde{\mathrm{r}}_{(i-1,j)}(t+k) + \sum_{k=-\mathrm{T1}}^{\mathrm{T2}} \beta_k \cdot \tilde{\mathrm{r}}_{(i,j-1)}(t+k) \qquad (1)$$

where α_k and β_k are proper weights, $[T1, T2]$ determine the length of the filter, and $\underline{\tilde{\mathrm{R}}}_{(i,j)} = [\tilde{\mathrm{r}}_{(i,j)}[0], \tilde{\mathrm{r}}_{(i,j)}[1], \ldots, \tilde{\mathrm{r}}_{(i,j)}[39]]$ is the decoder's reconstruction of the excitation signal; then residual error

$$\underline{\mathbf{E}}_{(i,j)} = \underline{\mathrm{R}}_{(i,j)} - \underline{\hat{\mathrm{R}}}_{(i,j)}$$

can be computed.

The weights α_k, β_k can either be obtained from an offline learning step via linear regression on a training set, or estimated online in a backward adaptive fashion. The first solution has the advantage of lower complexity, although the weights might not be universal and might not be optimal on a particular signal.

The prediction residual can then be quantized and sent to the decoder. The encoder performs its prediction using information shared with the decoder; i.e., information that the decoder has already received, such as the previously encoded frames from the signals above and on the left if the matrix is processed in raster scan order. Moreover, for the same reason, prediction must use the decoder's reconstruction of those signals even at the encoder.

Finally, the prediction residual error $\underline{\mathbf{E}}_{(i,j)}$ is quantized using an algebraic codebook as in regular ACELP, thus seeking for a representation constituted by a number (10 in this study) of unitary impulses and a gain. The quantization index, indicating the location and the sign of the impulses is then sent to the decoder along with the gain.

The total number of bits per 160-samples frame of an inner signal is 173, thus achieving a compression ratio of approximately 91% (about 1÷9).

4. TEST SIGNALS

The proposed compression algorithm has been tested on experimental surface EMG multi-channel recordings using a 13-bit residual LSF vector quantizer and T1=T2=3.

Surface EMG signals were detected from the dominant biceps brachii muscle of ten healthy male volunteers (mean age ±SD: 27.7 ± 2.3 years) with a matrix of 61 electrodes (diameter 1.27 mm; RS 261-5070, Milan, Italy; 5-mm interelectrode distance) arranged in 13 rows and 5 columns without the four corner electrodes. The subject sat on a chair with the back at 90° at the hip joint, the arm 90° flexed (0° abduction), and the elbow flexed at 120°. The subject was asked to produce three maximal voluntary contractions (MVCs) for 3-5 s each. After 10-min rest, the subject produced a contraction at 50% MVC lasting 20 s

5. SIGNAL ANALYSIS

The Signal-To-Noise ratio, Root Mean Square (RMS), Average Rectified Value (ARV), mean and median power spectral frequencies were estimated from the original and compressed EMG signals for each electrode at position $(i, j) \in [1, W] \times [1, H]$ in a $W \times H$ multi-channel recording.

ARV and RMS were computed as:

$$\mathrm{ARV} = \frac{1}{M} \sum_{n=1}^{M} |s[n]|, \tag{2}$$

$$\mathrm{RMS} = \sqrt{\frac{1}{M} \sum_{n=1}^{M} s^2[n]}, \tag{3}$$

where M is the number of signal samples.

Mean and median frequency were computed as:

$$f_{\mathrm{mean}} = \frac{\sum_{k=1}^{+N} f_k P[f_k]}{\sum_{k=1}^{+N} P[f_k]} \ \mathrm{Hz}, \tag{4}$$

$$\sum_{k=1}^{f_{\mathrm{med}}} P[f_k] = \sum_{k=f_{\mathrm{med}}}^{+N} P[f_k] = \frac{1}{2} \cdot \sum_{k=1}^{+N} P[f_k]. \tag{5}$$

Spectral variables (mean and median frequencies) were computed from 1-s signal epochs using the periodogram estimator of the power spectrum and the relative change in these parameters with compression was used to quantify the modifications in spectral features due to the loss of information.

Finally, the average Signal-To-Noise ratio in signal reconstruction was defined as:

$$\mathrm{SNR} = 10 \cdot \log \left(\frac{\sum_{i,j} \sum_{t=1}^{N} s^2_{(i,j)}[t]}{\sum_{i,j} \sum_{t=1}^{M} (s_{(i,j)}[t] - \hat{s}_{(i,j)}[t])^2} \right) \ \mathrm{dB}, \tag{6}$$

where $s_{(i,j)}$ and $\hat{s}_{(i,j)}$ are the original and reconstructed signals from electrode $(i, j), \forall (i, j) \in [1, W] \times [1, H]$.

The SNR provided a global indication of the average quality of multi-channel signal reconstruction.

6. RESULTS

The proposed technique was compared with the LSF-only method proposed in [7].

Table 1 describes the results in terms of the average SNR (defined by Eq. (6)) along with the percentage error (± standard deviation), averaged over all the signals in the multi-channel recording, for the selected variables as computed from Eq. (2) and Eq. (3) describing reconstruction of the waveform with respect to the original, uncoded signal for both [7] and the proposed technique, while Table 2 shows the corresponding information for what concerns the mean and median frequency of the spectrum computed using Eq. (4) and Eq. (5). The results in both tables are the average errors in the reconstruction as measured over the whole matrix.

The proposed technique achieves a slightly higher compression ratio than [7], because no longer term correlation is modeled and the corresponding LTP parameters do not need to be saved. However, on average, the performance in terms of SNR is about 3.2 dB higher resulting in a considerably more faithful signal reconstruction. Amplitude and spectral variables extracted from the surface EMG are similarly and negligibly affected by the two compression schemes.

7. CONCLUSIONS

We extended the coding technique for multi-channel surface EMG signals proposed in [7] to better exploit the correlation between adjacent signals in multi-channel EMG recordings.

Signal	SNR		ARV		RMS	
	Technique in [7] (dB)	Proposed technique (dB)	Technique in [7] (%)	Proposed technique (%)	Technique in [7] (%)	Proposed technique (%)
Cg_1_1	14.99	16.50	1.02 ± 0.13	1.36 ± 0.87	1.00 ± 0.08	1.17 ± 0.63
Df_1_1	16.37	21.06	0.98 ± 0.10	1.34 ± 0.50	1.02 ± 0.10	1.21 ± 0.35
Em_1_1	15.40	18.97	1.05 ± 0.13	1.51 ± 0.67	1.05 ± 0.14	1.42 ± 0.49
Lm_1_1	14.80	17.97	1.14 ± 0.14	1.39 ± 0.71	1.08 ± 0.13	1.33 ± 0.52
Mg_1_1	13.41	14.58	1.24 ± 0.22	1.76 ± 1.05	1.17 ± 0.24	1.68 ± 0.75
Sm_1_1	16.05	19.06	0.97 ± 0.10	1.28 ± 0.67	0.99 ± 0.10	1.12 ± 0.48
Sr_1_1	15.98	21.01	1.01 ± 0.11	1.41 ± 0.59	1.02 ± 0.12	1.25 ± 0.44
Average	15.26	18.45	1.06	1.44	1.05	1.31

Table 1. Average SNR, ARV and RMS (Eq.(6), (2), (3)) results are shown for experimental EMG signal matrices from the dominant biceps brachii muscles of different subjects during three contractions at 100% followed by one at 50% MVC. For each 5×12 signal matrix the percentage error averaged over the whole matrix is indicated along with the standard deviation.

Signal	f_{mean}		f_{med}	
	Technique in [7] (%)	Proposed technique (%)	Technique in [7] (%)	Proposed technique (%)
Cg_1_1	1.36 ± 0.37	1.53 ± 0.84	1.54 ± 0.28	1.60 ± 0.43
Df_1_1	1.14 ± 0.35	0.79 ± 0.37	1.18 ± 0.24	0.95 ± 0.23
Em_1_1	1.67 ± 0.64	1.44 ± 0.69	1.45 ± 0.62	1.02 ± 0.45
Lm_1_1	1.43 ± 0.36	1.41 ± 0.49	1.53 ± 0.36	1.22 ± 0.47
Mg_1_1	1.94 ± 0.45	1.94 ± 0.66	1.74 ± 0.49	1.59 ± 0.49
Sm_1_1	1.12 ± 0.33	0.95 ± 0.48	1.30 ± 0.29	1.16 ± 0.30
Sr_1_1	1.25 ± 0.44	0.99 ± 0.51	1.03 ± 0.26	0.78 ± 0.19
Average	1.42	1.29	1.38	1.19

Table 2. Average mean and median frequencies (Eq. (4), (5)) results are shown for experimental EMG signal matrices from the dominant biceps brachii muscles of different subjects, during three contractions at 100%MVC followed by one at 50% MVC. For each 5×12 signal matrix the percentage error averaged over the whole matrix is indicated along with the standard deviation.

The results on experimental signals showed that the method allows for high compression factor with lower signal distortion than previously achieved. An increase of approximately 3.2 dB of average Signal-to-Noise Ratio was obtained while maintaining comparable performance in terms of estimation of amplitude and spectral features of the surface EMG signal.

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