ACELP-BASED COMPRESSION OF MULTI-CHANNEL SURFACE EMG SIGNALS

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ABSTRACT

In this paper we extend a lossy compression technique for surface EMG signals, which is based on the Algebraic Code Excited Linear Prediction (ACELP) paradigm, to compress multi-channel surface EMG recordings by exploiting the correlation between the Line Spectral Frequencies (LSF). Experimental results show that the LSFs of the inner signals in a multi-channel recording can be efficiently represented with 13 bit/frame, versus the 38 bit/frame needed by independent ACELP coding of each signal, thus saving 66% of the bandwidth needed to transmit these coefficients while maintaining comparable performance in terms of the SNR, Average Rectified Value and Root Mean Square of the waveform, and mean and median frequencies of the power spectrum.

Index Terms— Data compression, Linear predictive coding

1. INTRODUCTION

Recordings of electromyographic (EMG) signals can have duration of hours when the muscle function has to be continuously monitored, as it happens when studying working activities [1]. Compression of this large amount of data is necessary such as when EMG data are acquired on a patient and sent to a nearby or to a remote computer for further processing and interpretation (telemedicine). Surface EMG signals are usually acquired at 12-16 bit/sample, at sampling rates ranging from 1 kHz to 10 kHz. Multi-channel surface EMG recordings are becoming increasingly interesting for researchers since they allow extraction of information concerning individual motor units, their peripheral and centrally controlled properties. Current technology allows the concomitant detection of hundreds of EMG signals from closely located positions over the skin. Although all the techniques cited above could be easily employed to compress each channel in a multi-channel EMG recording, better performance should be expected if correlation between adjacent channels is exploited.

Despite the importance of the possible applications, there are only few works dealing with compression of surface EMG signals, and, to our knowledge, none of them explicitly deals with multi-channel EMG recordings, where matrices of sensors are applied to a muscle, acquiring many correlated signals which have to be stored or transmitted.

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].

A single-channel EMG compression technique attaining high compression factors was presented in [6]. The technique is based on the Auto Regressive (AR) model theory and attains accurate reconstruction of the spectrum of the signal, but the waveform is not preserved, while in [7] AR modeling is followed by analysis-by-synthesis quantization of the residual error to allow for reconstruction of the waveform.

In this paper we present a surface EMG compression technique which exploits the correlation between the spectra of adjacent signals in a multi-channel recording, by means of predictive vector quantization.

The rest of this paper is organized as follows: single-channel [7] is briefly reviewed in Section 2, then the proposed technique is presented in Section 3; the signals used as a test set for the proposed algorithm are described in Section 4, and the relevant features in Section 5; in Section 6 results are presented; finally conclusions are drawn in Section 7.

2. REVIEW OF SINGLE-CHANNEL EMG SIGNALS CODING WITH ACELP

In previous works, the widely used speech compression approach known as Algebraic Code Excited Linear Prediction (ACELP) was selected to compress EMG 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.

Along this line, the surface EMG signal is divided into 160-sample frames without pre-processing; each of them is further divided into 40-sample subframes corresponding to 39.06 ms for a sampling frequency $f_s = 1$ kHz. The AR parameters are computed on these subframes.

In [7], where a widely adopted incarnation of ACELP, the GSM-AMR speech coding standard at 12.2 kb/s is used, the coefficients of the 10-tap STP filters are computed for the first and the third subframes. The parameters for the remaining two subframes are estimated through interpolation of the temporally adjacent ones. These STP coefficients are, in general, floating point-valued and do not lend themselves to straightforward quantization, so they are first transformed to an alternate representation, called the Line Spectral Frequencies (LSF). LSFs are more robust to quantization error and, moreover, allow easy check for filter stability after quantization. To further reduce the bitrate needed to save the LSFs, GSM-AMR 12.2 does not quantize them directly but, instead, the residual error of first-order MA prediction is vectorially quantized and sent to the decoder. Since direct quantization of the whole vector of LSFs would be computationally very demanding, the whole vector is split into subvectors consisting of adjacent pairs of LSFs from the first and the third subframe; each subvector is quantized independently and the quantization index sent to the decoder.

Longer term correlation, for example related to signal periodicity, is then modeled by means of the Long Term Predictor (LTP) filter. The LTP filter is parametrized as a gain and a delay. The parametrization of the LTP filter is performed by searching a number of past excitation residual signals (adaptive codebook) using the estimated correlation and then interpolating around its maximum so that non-integer pitch periods up to a 1/6th lag precision are considered. The LTP delay is absolutely coded for the first and the third subframes while for the other two subframes only the difference with respect to the preceding one is coded. It was expected that the LTP filter, introduced in speech to deal with the periodicity of voiced sounds, may be useful in the EMG case when low force contraction levels are considered since in this case the action potentials of single motor units repeat almost periodically. After STP and LTP prediction, the 40-sample residual excitation is vector quantized by exhaustive search on a codebook (the innovative codebook) which is designed to minimize the overall reconstruction distortion. To speed up quantization and reduce complexity, ACELP uses an algebraic codebook where the reconstruction vectors consist of a few unitary pulses, the number of which depends on the desired output bit rate, so that the complex operation of vector quantization consists in finding the proper position of the pulses to minimize reconstruction distortion as measured by the Mean Squared Error (MSE). The quantization indices thus represent the position and sign of those pulses.

3. COMPRESSION ALGORITHM

Multi-channel surface EMG signals are usually acquired using a rectangular array of sensors (usually aligned with the muscle axes), each recording the signal due to a contraction of the muscle at a different spatial position.

In this paper we concentrate on reducing the bitrate devoted to LSF quantization exploiting the correlation between adjacent signals in an EMG multi-channel recording by substituting first order MA prediction of the LSF coefficients with a predictor taking into consideration the corresponding coefficients from spatially adjacent signals. In fact, the spectra of spatially adjacent signals (in the form of the 10 LSF coefficients per 40-samples subframe) appears to be very correlated, thus allowing for a better form of DPCM encoding of the spectrum for the *inner signals* of an electrodes's matrix, i.e., whose neighboring channels have already been coded. If the reference signals are chosen with respect to a causal context of the signal to be coded, the decoder can simply invert the operations performed by the encoder and can faithfully reconstruct the signal.

Thus, given 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, the *l-th* $\mathrm{LSF}_{l,t}(i, j)$, at time frame t, subframe $s, s \in \{1, \cdots, 4\}$, a prediction can be formed as:

$$\begin{aligned}\mathrm{L\hat{S}F}_{l,t}^{(s)}(i,j) = \alpha_l \cdot \mathrm{LSF}_{l,t}^{(s)}(i-1,j) + \\ \beta_l \cdot \mathrm{LSF}_{l,t}^{(s)}(i,j-1) + \\ \gamma_l \cdot \mathrm{LSF}_{l,t-1}^{(s)}(i,j);\end{aligned} \tag{1}$$

where $\alpha_l, \beta_l, \gamma_l$ are proper weights which can be learned offline through linear regression on a training set; then residual error

$$\underline{\mathbf{E}}_{l,t}^{(s)} = (e_1^{(s)}, \cdots, e_l^{(s)}) = \underline{\mathrm{LSF}}_{l,t}^{(s)}(i,j) - \underline{\mathrm{L\hat{S}F}}_{l,t}^{(s)}(i,j)$$

is computed for the first and the third subframes.

The residual error vectors, $\underline{\mathbf{E}}_{l,t}^{(1)} = (e_1^{(1)}, \cdots, e_l^{(1)})$, and $\underline{\mathbf{E}}_{l,t}^{(3)} = (e_1^{(3)}, \cdots, e_l^{(3)})$ have to be quantized before transmission; to reduce the computational requirements of vectorial quantization of the whole residual vectors, five subvectors $\underline{\mathbf{S}}_k = (e_{2k-1}^{(1)}, e_{2k}^{(1)}, e_{2k-1}^{(3)}, e_{2k}^{(3)}), k \in [1, l/2]$ with elements belonging to both the vectors are independently quantized, similarly to what is done in regular ACELP. The quantizers have to be trained offline so as to minimize the reconstruction error on a training set of multi-channel EMG signals.

Since correlation is efficiently removed by the prediction step, quantization of the residuals can be coarse with respect to regular ACELP, thus achieving a substantial reduction in the bandwidth needed to faithfully transmit the LFSs coefficients. We experimentally found that quantization of these five subvectors with five vector quantizers using, respectively, $2+3+3+3+2 = 13\ \mathrm{bit/frame}$ yielded comparable performance with respect to [7] which used 38 bit/frame to convey a signal with the same spectral information and comparable error in the reconstruction of the waveform.

4. TEST SIGNALS

The proposed compression algorithm has been tested on a number of experimental surface EMG multi-channel recordings using a 13-bit residual LSF vector quantizer.

4.1. Experimental procedures

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 inter-electrode 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:

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

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

We compared our technique to independent ACELP coding of each signal in a multi-channel EMG recording and measured the average distortion of the reconstruction for both techniques.

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 two techniques achieve almost the same performance in terms of distortion introduced in the reconstruction, but the proposed technique reduces the bandwidth needed to transmit the spectral information from 38 bit/frame to 13 bit/frame, for the inner signals in a multi-channel recording.

7. CONCLUSIONS

We extended a coding technique widely used for speech signal compression to the compression of multi-channel surface EMG signals to exploit the correlation between the Line Spectral Frequencies (LSFs) of adjacent signals. The results on experimental signals showed that the method allows for high compression factor with limited signal distortion. In some applications, the amplitude variables and spectral features of the surface EMG signal are the only relevant information. In this study, it has been shown that these variables can be preserved with a percentage error smaller than 2% for experimental signals. This error is the same range of values as the standard deviation of estimation of amplitude and spectral variables.

Signal	SNR		ARV		RMS	
	Technique in [7] (dB)	Proposed technique (dB)	Technique in [7] (%)	Proposed technique (%)	Technique in [7] (%)	Proposed technique (%)
Cg_1_1	14.96	14.99	1.05 ± 0.12	1.02 ± 0.13	1.03 ± 0.11	1.00 ± 0.08
Df_1_1	16.34	16.37	0.99 ± 0.10	0.98 ± 0.10	1.04 ± 0.10	1.02 ± 0.10
Em_1_1	15.45	15.40	1.05 ± 0.12	1.05 ± 0.13	1.06 ± 0.13	1.05 ± 0.14
Lm_1_1	14.80	14.80	1.08 ± 0.10	1.14 ± 0.14	1.05 ± 0.08	1.08 ± 0.13
Mg_1_1	13.40	13.41	1.22 ± 0.20	1.24 ± 0.22	1.16 ± 0.19	1.17 ± 0.24
Sm_1_1	16.03	16.05	0.98 ± 0.10	0.97 ± 0.10	1.02 ± 0.10	0.99 ± 0.10
Sr_1_1	16.04	15.98	1.00 ± 0.10	1.01 ± 0.11	1.03 ± 0.12	1.02 ± 0.12

Table 1. Average SNR, ARV and RMS (Eq.(6), (2), (3)) results are shown for experimental EMG signal matrices from different subjects. For each 5×12 signal matrix the percentage error averaged over the whole matrix is indicated along with the corresponding standard deviation.

Signal	$\mathrm{f_{mean}}$		$\mathrm{f_{med}}$	
	Technique in [7] (%)	Proposed technique (%)	Technique in [7] (%)	Proposed technique (%)
Cg_1_1	1.34 ± 0.35	1.36 ± 0.37	1.45 ± 0.32	1.54 ± 0.28
Df_1_1	1.11 ± 0.33	1.14 ± 0.35	1.16 ± 0.20	1.18 ± 0.24
Em_1_1	1.58 ± 0.57	1.67 ± 0.64	1.40 ± 0.51	1.45 ± 0.62
Lm_1_1	1.38 ± 0.35	1.43 ± 0.36	1.51 ± 0.36	1.53 ± 0.36
Mg_1_1	1.87 ± 0.43	1.94 ± 0.45	1.75 ± 0.48	1.74 ± 0.49
Sm_1_1	1.11 ± 0.28	1.12 ± 0.33	1.26 ± 0.30	1.30 ± 0.29
Sr_1_1	1.22 ± 0.38	1.25 ± 0.44	1.02 ± 0.23	1.03 ± 0.26

Table 2. Average mean and median frequencies (Eq. (4), (5)) results are shown for experimental EMG signal matrices from different subjects. For each 5×12 signal matrix the percentage error averaged over the whole matrix is indicated along with the corresponding standard deviation.

In conclusion, the proposed approach allows for efficient coding and decoding with modest algorithmic delay of multichannel EMG signals saving $\sim 66\%$ of the bandwidth needed to transmit the LSF coefficients of inner signals of a multichannel recording, while maintaining almost the same performance as independent coding of each signal. The error in estimation of EMG variables is considered acceptable since it is comparable with the variability in estimation of these variables. Future work includes studying the correlation between other ACELP parameters for spatially adjacent signals and exploiting that correlation to design an highly multi-channel EMG compression algorithm.

8. REFERENCES

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