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Compression of surface EMG signals with algebraic code excited linear prediction

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Abstract

Despite the interest in long timescale recordings of surface electromyographic (EMG) signals, only a few studies have focused on EMG compression. In this paper we investigate a lossy coding technique for surface EMG signals that is based on the algebraic code excited linear prediction (ACELP) paradigm, widely used for speech signal coding. The algorithm was adapted to the EMG characteristics and tested on both simulated and experimental signals. The coding parameters selected led to a compression ratio of 87.3%. For simulated signals, the mean square error in signal reconstruction and the percentage error in average rectified value after compression were 11.2% and 4.90%, respectively. For experimental signals, they were 6.74% and 3.11%. The mean power spectral frequency and third-order power spectral moment were estimated with relative errors smaller than 1.23% and 8.50% for simulated signals, and 3.74% and 5.95% for experimental signals. It was concluded that the proposed coding scheme could be effectively used for high rate and low distortion compression of surface EMG signals. Moreover, the method is characterized by moderate complexity (approximately 20 million instructions/s) and an algorithmic delay smaller than 160 samples (∼160 ms).

Keywords: Electromyography; Compression; Spectral features

1. Introduction

Recordings of electromyographic (EMG) signals can have duration of hours when muscle function needs to be continuously monitored, as in the monitoring of working activities [15]. Compression of a large amount of data is necessary in many situations, such as when EMG data are acquired on a patient and sent remotely for processing and analysis (telemedicine) [19]. Surface EMG signals are usually acquired at 12–16 bits/sample, with sampling rate ranging from 1 kHz to 10 kHz. In addition, several types of detection systems can be applied to the same subject and/or muscle, leading to multi-channel recordings [13,18].

Extensive work on signal compression has been performed in related fields, such as in the electrocardiogram (ECG) [10] or electroencephalogram (EEG) [2] research areas. However, despite the importance of the potential applications, there are still few studies dealing with the compression of surface EMG signals. Norris and Lovely [17] investigated lossy compression of EMG signals using adaptive differential pulse code modulation (ADPCM), a technique commonly applied to speech signals. Their technique achieved a reduction in bit rate from 12 bits/sample to 4 bits/sample (compression factor ∼67%). Guerrero and Mailhes [7] compared the performance of compression techniques commonly used for speech signal coding (such as transform-based techniques comprising discrete wavelet transforms, discrete cosine transform, differential pulse code modulation, code excited linear prediction, and multi-pulse coder) applied to EMG signals. The use of wavelets has been suggested for intramuscular EMG

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signal compression [20]. The embedded zero-tree wavelet (EZW) coding was also applied to surface EMG signals [16], with compression ratios in the range 60–95%. More recently, Carotti et al. [3] proposed an EMG signal compression technique based on autoregressive (AR) modeling. This technique provides high compression ratios (over 97%) but it is not applicable if the shape of the signal waveform has to be preserved after compression.

In this paper we modified a speech signal compression technique that performs autoregressive (AR) modeling followed by analysis-by-synthesis quantization of the residual error to allow for reconstruction of the original waveform. This coding technique aims to achieve a low algorithmic delay and low bit rate while preserving to a sufficient degree of accuracy both the waveform of the signal and important EMG variables related to the time (such as the average rectified value, ARV, and the root mean square, RMS) and the spectral domain representation of the signal.

2. Methods

2.1. Compression algorithm

The proposed coding technique is based on the algebraic code excited linear prediction (ACELP) method [1], which is widely applied for coding speech signals, e.g., in the global system for mobile adaptive multi rate (GSM-AMR) speech coder [4]. For speech applications, the ACELP coder computes the parameters of an AR model of the input speech signal (sampled at 8 kHz, 12 bits/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. Long-term correlation, such as that related to the signal quasi-periodicity of voiced speech segments, is then modelled by means of the long-term predictor (LTP) filter (Fig. 1).

The two predictor filters ensure that the signal spectrum is faithfully reconstructed but the signal waveform cannot be correctly recovered unless the proper excitation signal is conveyed to the decoder. For this purpose, the residual error signal from the two filters is vector quantized with an analysis-by-synthesis approach that minimizes the mean squared error (MSE) between the original and the synthesized signals. The quantization index is sent together with the filter parameters to the decoder.

2.1.1. ACELP coder for EMG signals

The GSM-AMR implementation of the ACELP coder compresses speech signals at eight bit rates ranging from 4.75 kb/s to 12.2 kb/s. In this study we adapted the 12.2 kb/s rate to the EMG application. The EMG signal was divided into 160-sample frames without pre-processing since this ensured a good trade-off between coding delay and coding performance. Tests, not shown, were performed with frame size up to 1024 samples and resulted in minimal differences in compression performance. Each EMG 160-sample frame was further divided into 40-sample subframes corresponding to approximately 39 ms. AR parameters were then computed on these subframes. For speech applications, the GSM-AMR ACELP coder applies high-pass filtering (cut-off frequency 80 Hz) and amplitude downscaling by a factor of 2, which are not appropriate for EMG signals.

It has been previously shown that the power spectral moments of the surface EMG can be obtained with negligible error using a 10-tap all pole filter [3], thus a 10-order STP was chosen. AR coefficients are estimated from the first and third subframes and interpolation is applied for the model parameters of the remaining subframes. The AR coefficients are computed from the signal autocorrelation [12]. Since the variance of the estimate of the autocorrelation function decreases

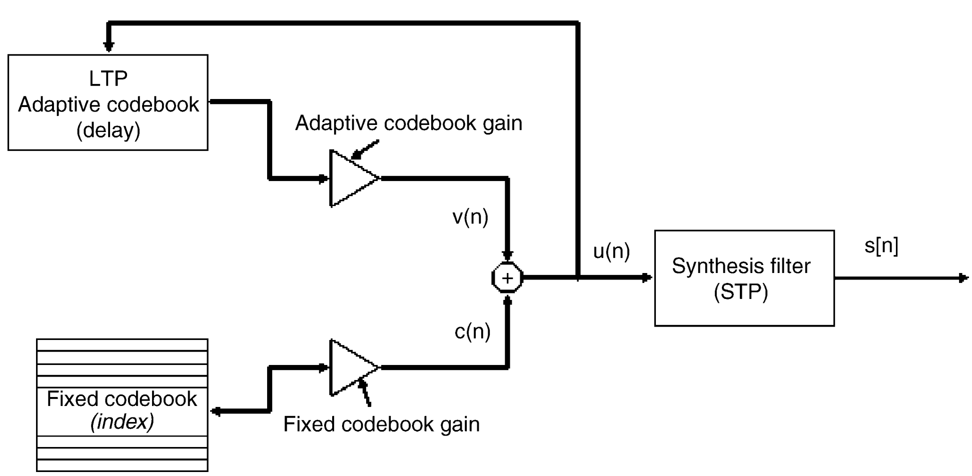

Fig. 1. Block diagram of the CELP synthesis model. The diagram depicts the main blocks and their interaction when a signal is synthesized. An excitation signal from the fixed codebook is selected using the quantization index sent by the encoder, amplified by the corresponding gain to generate the signal c[n]. c[n] is combined with the output of the LTP filter v[n] which includes filtered past residuals to make a proper excitation signal for the STP synthesis filter which reconstructs the signal.

with the number of samples used for its estimate, we used a 240-sample window for estimation of the autocorrelation. Prior to computing the STP filter's parameters, the signal was windowed with a modified Hamming asymmetric window. For the first filter, the window was chosen to weigh more the samples in the first half of the frame, while for the second filter more weight was given to the second half of the frame.

Finally, the floating point AR coefficients were transformed into the line spectral pairs (LSP) representations [9] to assure quantization and interpolation efficiency as well as filter stability. The two STP filters are then jointly quantized with split matrix quantization of a first-order moving average (MA) prediction residual [21]. The GSM-AMR speech coder also uses a 40-sample overhead to estimate the STP coefficients but this introduces a 40-sample delay at the decoder that is undesirable for EMG signals and thus has been omitted.

The LTP filter models longer term signal correlations and is parametrized as a gain and a delay (which, for speech, corresponds to the quasi-periodicity of voiced sounds due to vocal cord vibration). The parametrization of the LTP filter is performed by searching a number of past excitation residual signals (adaptive codebook) in two stages: first an open-loop estimate of the pitch is computed by inverse filtering the original signal with the LPC coefficients, then closed-loop pitch search is performed around the open-loop estimate. Closed-loop pitch search is based on the analysis-by-synthesis approach and is aimed at minimizing the final reconstruction error. Pitch search is conducted in the range 20–123 samples, i.e., ∼20–120 ms. The LTP delay is coded for the first and third subframes while for the other two subframes only the (usually small) difference with respect to the preceding subframe is coded. Results (not shown) on EMG proved that, after LTP prediction, the residual signal was white and with a lower energy than the input STP residual.

After STP and LTP prediction, the 40-sample subframe residual excitation is vector quantized by exhaustive search on a codebook (the innovative codebook) that 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 MSE. The quantization indices thus represent the position and sign of those pulses. A 35-bit codebook was used to code the position and sign of 10 such pulses. A summary of the overall bit allocation for one frame is reported in Table 1.

The decoder inverts the process and reconstructs the signal by inverse filtering the excitation signal from the innovative codebook through the LTP and STP filter. Due to filter memory the reconstructed signal is continuous across subframes. The post-processing stage used by the GSM-AMR coder to enhance the perceived subjective quality of the reconstruction at the expense of signal-to-noise ratio (SNR) was omitted for the EMG application.

Table 1
Bit allocation for a 160-sample frame (see text for definition of parameters)

Parameter	Subframe				Total
	1	2	3	4	
LSF					38
Adaptive codebook	9	6	9	6	30
Adaptive gain	4	4	4	4	16
Algebraic codebook	35	35	35	35	140
Algebraic gain	5	5	5	5	20
Total bits/frame					244

2.2. Test signals

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

2.2.1. Simulation of surface EMG signals

Surface EMG signals were simulated with the model described in [6]. The model produces synthetic motor unit action potentials generated by muscle fibres of finite length and detected by surface electrodes. The volume conductor comprises the muscle, fat and skin tissues, separated by planar layers. The physical parameters of the model were selected as in [6]. Sixty-five motor units with number of fibres in the range 50–600 (uniform distribution) were located in random positions inside the muscle. The motor units were recruited according to the size principle [8] and were assigned conduction velocities with Gaussian distribution (mean 4 m/s, standard deviation 0.3 m/s). The recruitment thresholds and modulation of discharge rate were simulated as previously described [11] with contraction forces in the range 10–70% of the maximal voluntary contraction (MVC) force (20% MVC increments). For each contraction force, five signals were generated with random allocation of the motor unit positions in the muscle.

2.2.2. Experimental procedure

Surface EMG signals were collected from the biceps brachii muscle of six male subjects (age, mean ± S.D., 25.3 ± 3.2 years) with a bipolar electrode system (bar electrodes, 5 mm long, 1 mm diameter, 10 mm interelectrode distance). The subject's arm was placed in an isometric brace and the forearm was fixed at 120° (180° being full extension of the forearm). The MVC was estimated as the maximum torque exerted in three trials separated by 3-min rest in between.

Each subject then performed four 15-s contractions at torque levels 10–70% MVC (20% MVC increments) with 10-min rest between contractions. The EMG signals were amplified (−3 dB bandwidth: 10–500 Hz), fed into a 12-bit acquisition board, and sampled at 2048 samples/s. The recorded signals were off-line band-pass filtered in the range 10–400 Hz and downsampled to 1024 Hz before compres-

Table 2
Average (±S.D.) reconstruction errors for simulated EMG signals

Force level	Waveform	Amplitude variables		Spectral features		
(% MVC)	MSE (Eq. (6))	% ARV (Eq. (2))	% RMS (Eq. (2))	% f_{mean} (Eq. (3))	% f_{med} (Eq. (4))	% Skewness (Eq. (5))
10	8.28 ± 0.66	7.49 ± 1.46	4.27 ± 0.69	1.37 ± 0.34	1.70 ± 0.47	12.05 ± 2.92
30	11.31 ± 0.22	3.03 ± 0.23	3.16 ± 0.19	1.27 ± 0.31	1.25 ± 0.40	6.41 ± 2.53
50	13.12 ± 2.30	5.19 ± 2.09	5.10 ± 2.10	1.15 ± 0.38	0.95 ± 0.70	8.72 ± 4.04
70	11.38 ± 1.15	3.90 ± 1.06	3.64 ± 0.73	1.12 ± 0.61	1.46 ± 0.81	6.84 ± 3.04

For each force level, results are reported over the five signals simulated in the same conditions with random location of the motor units within the muscle (see text for details). MSE: mean square error; ARV: average rectified value; RMS: root mean square value; f_{mean}: mean frequency; f_{med}: median frequency.

sion. The compression factor was computed with reference to 1024 Hz sampling rate.

2.2.3. Signal analysis

With the selected parameters, a fixed compression factor of 87.3% was achieved in all conditions. This can be increased with changes in the implementation of the algorithm but in this study only results with this compression factor are presented. Compression factor was defined as:

$$C = 100\frac{L_{\text{input}} - L_{\text{output}}}{L_{\text{input}}}\% \tag{1}$$

where L_{input} and L_{output} are the original and the compressed file lengths, respectively.

RMS, ARV, mean power spectral frequency, median frequency and spectral skewness [14] were estimated from the original and compressed EMG signals. ARV and RMS were computed as:

$$\text{ARV} = \frac{1}{M}\sum_{n=1}^{M}|s[n]| \qquad \text{RMS} = \sqrt{\frac{1}{M}\sum_{n=1}^{M}s^2[n]} \tag{2}$$

where M is the number of signal samples.

Mean and median frequencies were computed as:

$$f_{\text{mean}} = \frac{\sum_{i=1}^{N} f_i P[f_i]\Delta f}{\sum_{i=1}^{N} P[f_i]\Delta f} \tag{3}$$

$$\sum_{i=1}^{f_{\text{med}}} P[f_i]\Delta f = \sum_{i=f_{\text{med}}}^{N} P[f_i]\Delta f = \frac{1}{2}\sum_{i=1}^{N} P[f_i]\Delta f \tag{4}$$

where $\Delta f = (f_i - f_{i-1})$ is the constant separation between frequency bins.

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

$$\mu_3 = \frac{M_{C3}}{M_{C2}^{3/2}} = \frac{\sum_{i=1}^{N}(f_i - f_{\text{mean}})^3 P[f_i]\Delta f}{\left(\sum_{i=1}^{N}(f_i - f_{\text{mean}})^2 P[f_i]\Delta f\right)^{3/2}} \tag{5}$$

Spectral variables were computed from 1-s signal epochs using the periodogram estimator of the power spectrum. The relative change in signal variables with compression was used to quantify the modifications in signal features due to the loss of information. The waveform distortion (D) introduced by the compression/decompression procedure was defined as the normalized percent MSE:

$$D = 100\frac{\sum_{i=1}^{N}(s_{\text{orig}}[i] - s_{\text{rec}}[i])^2}{\sum_{i=1}^{N} s_{\text{orig}}^2[i]} \tag{6}$$

between the original signal s_{orig} and the reconstructed signal s_{rec}.

3. Results

Table 2 shows the performance indexes for compression of the simulated EMG signals at the four excitation levels. Results are reported as average and standard deviation over the five signal realizations for each excitation level. Fig. 2 shows an example of compressed experimental EMG signal and Table 3 reports performance indexes for the experimental signals. Percent variation of all indexes is below 10%. The reconstruction error and relative error in amplitude variables are in general larger in simulation than for experimental signals while mean and median frequency have smaller error for simulated than experimental signals.

Table 3
Average (±S.D.) reconstruction errors for experimental EMG signals

Force level	Waveform	Amplitude variables		Spectral features		
(% MVC)	MSE (Eq. (6))	% ARV (Eq. (2))	% RMS (Eq. (2))	% f_{mean} (Eq. (3))	% f_{med} (Eq. (4))	% Skewness (Eq. (5))
10	9.17 ± 1.55	5.30 ± 0.70	4.30 ± 1.32	5.69 ± 2.21	3.10 ± 1.05	6.87 ± 3.94
30	6.59 ± 1.80	2.78 ± 1.12	2.29 ± 1.22	3.47 ± 0.88	2.24 ± 1.20	5.08 ± 0.65
50	5.95 ± 1.40	2.33 ± 1.40	1.99 ± 0.90	2.88 ± 0.49	1.83 ± 0.88	5.77 ± 0.95
70	5.26 ± 1.20	2.05 ± 1.65	1.72 ± 0.52	2.94 ± 0.83	1.95 ± 0.58	6.07 ± 1.37

For each force level, results are reported over six subjects. MSE: mean square error; ARV: average rectified value; RMS: root mean square value; f_{mean}: mean frequency; f_{med}: median frequency.

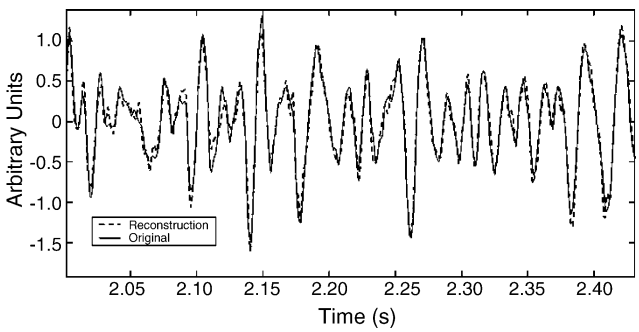

Fig. 2. A portion of an experimental EMG signal prior to compression and after decoder's reconstruction. The signal corresponds to a 70% MVC contraction and the reconstruction led to MSE of 3% with respect to the original signal (with compression factor 87.3%).

4. Discussion

We adapted a coding technique widely used for speech compression to the compression of surface EMG signals. The results on simulated and experimental signals showed that the method achieves high compression factors 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 10% for experimental recordings. This error is in the same range of values of the standard deviation of estimation of amplitude and spectral variables. For example, Farina and Merletti [5] showed, on synthetic signals, that mean and median power spectral frequencies can be estimated from surface EMG with a relative standard deviation of 3% and 7% of the true value, respectively. Thus, the variability of spectral variable estimates due to the stochastic nature of the surface EMG are larger than the percentage errors obtained in this study after compression by a factor of 87.3%.

If only amplitude and spectral variables are of interest, however, a simpler compression scheme may be preferable. We previously showed that spectral moments of the surface EMG can be preserved with a relative error smaller than 10% with compression factors up to 97% [3]. With the method proposed by Carotti et al. [3], however, only the spectral shape was preserved which is not acceptable in applications where further analysis of the signal is desirable after compression. The present approach preserves the signal shape at the price of a lower compression factor than in [3] (87.3% vs. 97.1% with similar errors in EMG variables after compression).

One of the main advantages of the proposed coding scheme is that the algorithmic delay is very small. The decoder waits for a frame to be completely received before synthesizing the reconstruction. In most transform-based techniques, such as DCT-based methods, longer blocks of data are packed and transformed prior to quantization and entropy coding, thus suffering from higher algorithmic delays.

In conclusion, the proposed approach allows for almost real time (∼160 ms delay) coding and decoding of EMG signals with average compression factors of 87.3% and reconstruction error of the waveform, defined as in Eq. (6), limited to less than 10% in experimental signals. The error in estimation of time- and spectral-domain EMG variables is considered acceptable since it is comparable with the variability in estimation of these variables. The method can thus be effectively used in long-term recordings, such as those performed over many hours in ergonomics and occupational medicine.

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