COMPRESSION OF SURFACE EMG SIGNALS WITH ALGEBRAIC CODE EXCITED LINEAR PREDICTION

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ABSTRACT

In this paper we investigate a lossy coding technique for surface EMG signals which 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. A fixed compression ratio of 87.3% was chosen. On simulated signals, the mean square error in signal reconstruction and the percentage error in average rectified value after compression were 10.43 % and 5.52 %, respectively. On experimental signals, they were 6.74% and 3.11%. The mean power spectral frequency and third order power spectral moment were estimated with relative error smaller than 1.36% and 1.70%, respectively, for simulated signals, and 3.74% and 2.28% for experimental signals. It was concluded that the proposed coding scheme can be effectively used for high rate, low distortion and low-delay compression of surface EMG signals.

1. INTRODUCTION

Recordings of electromyographic (EMG) signals can have duration of hours when the muscle function has to be continuously monitored, as it happens during working activities [1]. Compression of this 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 and/or muscle, leading to multi-channel recordings. Despite the importance of the possible applications, there are only few works dealing with compression of surface EMG signals.

Norris *et al.* [2] investigated lossy compression of 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 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[4]. The embedded zero-tree wavelet (EZW) coding, was also applied to EMG signals[5].

An EMG compression technique attaining high compression factors was presented in [6]. The technique was based on the Auto Regressive (AR) model theory and attained accurate reconstruction of the spectrum of the signal, while the waveform was not preserved.

Along that line, in this paper we modified a speech signal compression technique, which performs AR modeling followed by analysis-by-synthesis quantization of the residual error to allow for reconstruction of the waveform, to EMG signal coding. This coding technique is aimed at achieving a low algorithmic delay and low bitrate while still preserving the waveform of the signal and important EMG variables relating both to the time domain representation of the signal and to the shape of its spectrum.

The rest of this paper is organized as follows: the proposed technique is presented in section 2; the signals used as a test set for the proposed algorithm are described in section 3, the relevant features in section 4; in section 5 results are presented; finally conclusions are drawn in section 6.

2. COMPRESSION ALGORITHM

We propose an EMG coding technique based on the Algebraic Code Excited Linear Prediction (ACELP) method, which is widely applied for coding speech signals, e.g., in the GSM-AMR speech coder[7]. For speech applications, the ACELP coder computes the parameters of an 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. Longer term correlation, for example related to signal periodicity, is then modeled by means of the Long Term Predictor (LTP) filter. 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. The quantization index is sent along with the filter parameters to the decoder.

2.1. ACELP coder for EMG signals

The GSM-AMR implementation of the ACELP algorithm encodes speech signals at eight bit rates, ranging from 4.75 kb/s to 12.2 kb/s. In this study we adapted 12.2 kb/s rate to the EMG application.

The EMG signal is divided into 160-sample frames without pre-processing; for speech applications the ACELP coder applies high-pass filtering with cut-off frequency 80 Hz and downscaling by a factor of two, which is not appropriate for EMG signals. Each EMG 160-sample frame is further divided into 40-sample subframes corresponding to 39 ms. The AR parameters are computed on these subframes.

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[6], thus a 10-order STP was chosen. AR coefficients are estimated from the first and the third subframes and interpolation is applied for the model parameters of the remaining subframes. The AR coefficients are computed from the signal autocorrelation[8]. Since the variance of estimation of the autocorrelation function depends on the number of samples used for its estimate, we used a 240-sample window for autocorrelation estimation. Finally, the floating point AR coefficients are transformed into the Line Spectral Pairs (LSP) representations to assure quantization and interpolation efficiency as well as filter stability. The two STP filters are then jointly quantized with split matrix quantization of 1st order Moving Average (MA) prediction LSF residuals[9].

The LTP filter models longer term signal correlations and 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 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 measure by the Mean Squared Error (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. 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. The post-processing stage used for audio applications to enhance the perceived quality of the reconstruction at the expense of the Signal-to-Noise Ratio (SNR) was omitted for the EMG application.

3. TEST SIGNALS

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

3.1. Experimental procedures

Experimental EMG signals were collected from the biceps brachii muscle of six male subjects (age, mean $\pm$ SD, 25.3 $\pm$ 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 120deg (180 being full extension of the forearm). The maximal voluntary contraction (MVC) torque 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 (increments of 20% MVC) 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 compression.

3.2. Simulation of surface EMG signals

Surface EMG signals were simulated using the model described in [10]. The model produces synthetic motor unit action potentials generated by muscle fibers 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 [10]. Sixty-five motor units with number of fibers 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 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. Contraction forces in the range 5%–45% MVC (increments

5% MVC) were simulated. For each contraction force, 5 signals were generated with random allocation of the motor unit positions in the muscle.

4. SIGNAL ANALYSIS

Envelope, Root Mean Square (RMS), Average Rectified Value (ARV), mean power spectral frequency, median frequency and spectral skewness[11] were estimated from the original and compressed EMG signals.

ARV and RMS were computed as:

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

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

where M is the number of signal samples.

Mean and median frequency were computed as:

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

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

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

$$\mu_3 = \frac{M_{C3}}{M_{C2}^{3/2}} = \frac{\sum_{i=1}^{+N}(f_i - f_{\mathrm{mean}})^3 P[f_i]\cdot(f_i - f_{i-1})}{(\sum_{i=1}^{+N}(f_i - f_{\mathrm{mean}})^2 P[f_i]\cdot(f_i - f_{i-1}))^{3/2}}. \tag{5}$$

Spectral variables 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 mean square error in signal reconstruction was defined as:

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

Mean square error provided a global indication of the quality of signal reconstruction.

Finally, compression factor was defined as:

$$C = 100\cdot\frac{L_{\mathrm{orig}} - L_{\mathrm{comp}}}{L_{\mathrm{orig}}}\%, \tag{7}$$

where L_{orig} and L_{comp} are, respectively, the original and the compressed file lengths.

5. RESULTS

With the selected parameters, a fixed compression factor of 87.29% is achieved. This can be increased with changes in the implementation of the algorithm but in this study only results with this compression factor are presented.

Table 1 shows the performance indexes for compression of the simulated EMG signals at the six excitation levels. Results are reported as average and standard deviation over the five signal realizations. Figure 1 shows an example of compressed experimental EMG signal. Table 2 reports the same indexes for the experimental signals. All indexes are below 10% with a tendency of decreased reconstruction error for increasing force level. The reconstruction error and relative error in amplitude variables are in general larger than for the case of experimental signals while mean and median frequency present smaller error than in the experimental case.

6. CONCLUSIONS

We adapted a coding technique widely used for speech signal compression to the compression of surface EMG signals. The results on simulated and 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 10% for experimental signals. This error is the same range of values as the standard deviation of estimation of amplitude and spectral variables. For example, Farina *et al.*[12] showed, on synthetic signals, that mean and median power spectral frequencies can be estimated with a relative standard deviation of approximately 7% and 3% of the real value. Thus, the variability of estimates due to the stochastic nature of the surface EMG are comparable with the percentage errors obtained in this study after compression by 87.3%. One of the main advantages of this coding scheme with respect to other approaches is that the algorithmic delay is kept low due to framing. The decoder waits for a frame to be completely received before synthesizing the reconstruction while for transform-based techniques, such as wavelet-based methods, longer blocks of data are usually packed and transformed prior to quantization and entropy coding, thus suffering from usually higher algorithmic delay.

In conclusion, the proposed approach allows for almost real time coding and decoding EMG signals with compression factor 87.3% and reconstruction error limited to less than 10%. The error in estimation of 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 in ergonomics and occupational medicine.

Force Level	Rec. error (%)	ARV	RMS	Spectral Features		
(% of MVC)				f_{mean}	f_{med}	Skewness (μ_3)
5	10.51 ± 2.14	8.19 ± 1.43	8.02 ± 3.86	2.08 ± 0.41	1.92 ± 0.23	11.13 ± 3.32
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
15	8.71 ± 0.80	6.57 ± 1.37	3.81 ± 0.23	1.08 ± 0.13	1.78 ± 0.30	13.63 ± 1.87
20	9.47 ± 1.01	4.50 ± 1.49	3.62 ± 0.54	1.20 ± 0.13	1.55 ± 0.27	10.44 ± 2.15
30	11.89 ± 0.69	2.41 ± 0.90	5.13 ± 0.56	1.16 ± 0.32	1.51 ± 0.17	8.66 ± 1.10
45	13.75 ± 1.06	3.93 ± 1.56	6.58 ± 0.90	1.25 ± 0.12	1.75 ± 0.36	8.02 ± 1.21

Table 1. Average coding results are shown for simulated EMG signals. For each force level the percentage error averaged over 6 different signals is indicated along with the corresponding standard deviation.

Force Level	Rec. error (%)	ARV	RMS	Spectral Features		
(% of MVC)				f_{mean}	f_{med}	Skewness (μ_3)
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

Table 2. Average coding results are shown for Experimental EMG signals. For each force level the percentage error averaged over 5 different subjects is indicated along with the corresponding standard deviation.

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