Compression of Multidimensional Biomedical Signals With Spatial and Temporal Codebook-Excited Linear Prediction

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***Abstract*—In this paper, we propose a model-based lossy coding technique for biomedical signals in multiple dimensions. The method is based on the codebook-excited linear prediction approach and models signals as filtered noise. The filter models short-term redundancy in time; the shape of the power spectrum of the signal and the residual noise, quantized using an algebraic codebook, is used for reconstruction of the waveforms. In addition to temporal redundancy, redundancy in the coding of the filter and residual noise across spatially related signals is also exploited, yielding better compression performance in terms of SNR for a given bit rate. The proposed coding technique was tested on sets of multichannel electromyography (EMG) and EEG signals as representative examples. For 2-D EMG recordings of 56 signals, the coding technique resulted in SNR greater than 3.4 ± 1.3 dB with respect to independent coding of the signals in the grid when the compression ratio was 89%. For EEG recordings of 15 signals and the same compression ratio as for EMG, the average gain in SNR was 2.4 ± 0.1 dB. In conclusion, a method for exploiting both the temporal and spatial redundancy, typical of multidimensional biomedical signals, has been proposed and proved to be superior to previous coding schemes.**

***Index Terms*—EEG, electromyography (EMG), lossy compression, multichannel signals.**

I. Introduction

MANY diagnostic and monitoring activities require long-duration recordings of biomedical signals, such as electromyography (EMG), ECG, or EEG. The amount of data to be transferred or stored may be very large. For example, surface EMG signals are usually acquired at 12–16 bits/sample, with sampling rate ranging from 1 to 10 kHz, and in some applications, are recorded continuously for hours, e.g., for monitoring muscles during working activities [1]. In addition, several types of detection systems can be applied on the same patient, leading to multichannel recordings [2], [3].

In some cases, the acquisition system is not directly connected to the processing system. This can be either the case of telemedicine or acquisition systems transferring data with wireless technology, which allows reducing the size of devices mounted on the subject, e.g., in ergonomics or sport-related studies. In these applications, signal compression is highly desirable to reduce the bandwidth needed to transmit or store the signals while preserving their relevant information content.

Extensive work has been performed on biomedical signal compression [3], [4]. Although in some cases, lossless techniques have been applied [5], the research has focused mostly on lossy coding. Lossy compression is preferred when the distortion introduced by the compression scheme does not affect the clinical relevance of the reconstructed signal. Several techniques have been previously proposed for lossy compression of single-channel biomedical signals (e.g., see [7]–[10]); these methods usually perform a transformation of the signal in a domain where the signal energy is distributed across a few coefficients. For example, Brechet *at al.* [11] recently proposed a lossy coding technique for single-channel biomedical signals based on the wavelet packet transform [discrete packet wavelet transform (DPWT)] and modified embedded zero-tree coding [embedded zero-tree wavelet (EZW)].

Single-channel coding techniques are based on removing the temporal redundancy in the signal. In multichannel recordings, in addition to temporal correlations within each channel, significant correlation may also be present across the channels; the spatial correlation depends on the nature of the signal sources and on the location of the detecting sensors. Exploiting the interchannel correlation would probably result in more efficient coding of the data with possibly lower distortion. However, relatively few studies have addressed compression of multichannel biomedical recordings [12].

Although, in principle, it would be possible to adapt compression techniques developed for video sequence coding to multidimensional biomedical signals, these methods would be suboptimal for the specific application. Biological signals, although significantly spatially correlated, can, indeed, be considered wide-sense stationary (WSS) for longer time intervals than video sequences, for which usually only neighboring frames are interpolated for prediction [13], [14]. For example, in static conditions surface, EMG signals are often considered WSS for time intervals of up to 1–2 s [15]; these signals can be efficiently modeled with antireflection (AR) all-pole filters of limited order [16], and thus, have characteristics more similar to speech or audio signals than to video sequences.

In this paper, we propose a new multidimensional compression technique based on AR modeling, and aim at exploiting both the temporal intrachannel and the spatial interchannel

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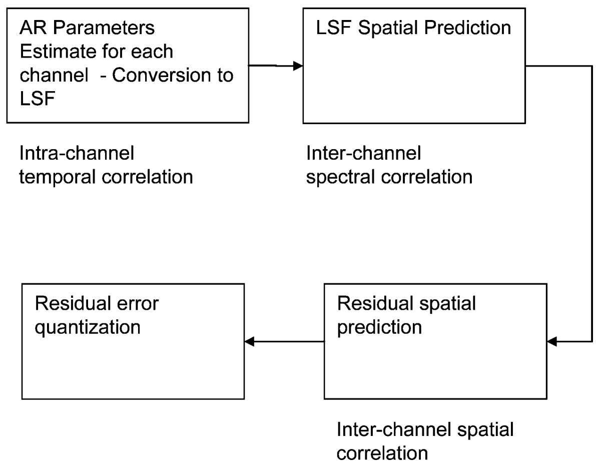

Fig. 1. Block diagram of the proposed technique. The AR model parameters are estimated for each channel, then the interchannel dependency is removed between both the LSF parameters and the prediction residual data using past coded data from spatially adjacent signals. The resulting residual error signal is vectorially quantized by means of analysis-by-synthesis. See text for details.

correlation of the signals. The technique can be applied to any multidimensional recording and will be tested on two representative examples of multichannel biomedical signals (EEG and EMG).

II. Methods

We assume to operate on multidimensional signals, with time as one of the dimensions; the other dimensions represent spatial information. For example, multichannel EEG and EMG signals have one temporal and two spatial dimensions. These recordings can be considered as a collection of correlated waveforms characterized by both temporal redundancy (within the single waveform) and spatial redundancy (across waveforms). Effective compression techniques should maximally reduce both types of redundancy.

Fig. 1 depicts a block diagram of the proposed technique, which is detailed in the following.

A. Temporal Redundancy

We first consider the temporal coordinate independently for each recorded signal. We will assume that each signal can be described by an AR model of adequate order. Under this assumption, single-channel signals can be compressed using a coding technique modified from the algebraic code excited linear prediction (ACELP) [20]–[22]. With this compression scheme, an AR model [called the short-term predictor (STP)] is used to describe the shape of the power spectrum of the signal (or, in the time domain, the short-term temporal correlation). Thus, a signal is divided into frames over which it can be considered WSS, and the parameters of the AR model are estimated from each frame. Reconstruction of the waveform is obtained using the AR coefficients and the excitation residual error signal. The residual error is then coded with an analysis-by-synthesis vector quantization method; thus, seeking for the codeword that minimizes the mean-squared error in the reconstruction of the signal.

In this study, the signals are divided into 160-sample frames, although different frame lengths are possible. Each 160-sample frame is further divided into 40-sample subframes. AR parameters are then computed from these subframes. The AR model order depends on the application. For example, an order of 10 was shown to be appropriate for surface EMG spectral description [7]. AR coefficients are estimated from the second and fourth subframes, and linear interpolation is applied for the model parameters of the remaining subframes, i.e., they are estimated as the means of the corresponding parameters from the preceding and the subsequent subframes, which are available to both the encoder and the decoder. The AR coefficients are computed from the signal autocorrelation [17]. Since the variance of the estimate of the autocorrelation function decreases with the number of samples used for its estimate, 80 samples were used for the estimation of the autocorrelation.

The floating point AR coefficients are transformed into the line spectral frequencies (LSF) representations to assure quantization and interpolation efficiency, and filter stability [18]. The two STP filters from the second and fourth subframes are then jointly quantized with split matrix quantization of a first-order moving average (MA) prediction residual [19]. Finally, the prediction residual signal of each 40-sample subframe is coarsely quantized into a number of unitary pulses and a gain by means of an algebraic codebook, and analysis-by-synthesis to minimize the mean-squared error of the whole reconstruction signal [21]. CELP coding of speech signals would perform an intermediate step, called long-term prediction (LTP), before quantization of the residual data, aimed at removing long-term redundancy due to the voice pitch [20], [22]. This characteristic is not present in the biomedical signals considered, and thus, the LTP was not included in the proposed method.

B. Spatial Correlation Across Power Spectra

Multidimensional recordings are usually not spatially white. Therefore, it is expected that better compression performance can be achieved if the spatial correlation across channels is exploited rather than coding each individual signal independently. Moreover, the power spectra of signals from different channels may be similar to each other.

From a multichannel recording, a neighborhood can be defined, sorting the signals according to the distance between detection locations. If the neighbors are chosen in a spatial causal context of the signal to be coded, i.e., a context including only previously coded data, the decoder will be able to perform the same computation as the encoder without adding delay. In the following, we will assume 2-D matrices of signals in raster scan order (top to bottom, and left to right), i.e., a neighborhood of signals on the left and above the one to be coded. The same method can also be applied to higher order spatial dimensions. In the assumption that the power spectra of the signals in a neighborhood are similar, spatial prediction over the LSFs can be used to differentially code these parameters. Given a generic single-channel signal at the spatial position (i, j), and the lth LSF parameter at time t and 40-sample subframe s, a prediction can be obtained using the decoder's reconstruction of already coded LSFs from spatially adjacent neighbors

$$\hat{\mathrm{LSF}}_{l,t}^{(s)} = \alpha_l \mathrm{LSF}_{l,t}^{(s)}(i-1,j) + \beta_l \mathrm{LSF}_{l,t}^{(s)}(i,j-1) + \gamma_l \mathrm{LSF}_{l,t-1}^{(s)}(i,j) \tag{1}$$

where α_l, β_l, and γ_l are the coefficients to be learned offline through linear regression on a training set of representative signals prior to coding, or adapted online on previously coded data. The coefficients are, thus, determined from the overdetermined system as

$$\begin{bmatrix} \mathrm{LSF}_{l,1}^{(s)}(0,1) & \mathrm{LSF}_{l,1}^{(s)}(1,0) & \mathrm{LSF}_{l,0}^{(s)}(1,1) \\ & \vdots & \\ \mathrm{LSF}_{l,T}^{(s)}(M-1,N) & \mathrm{LSF}_{l,T}^{(s)}(M,N-1) & \mathrm{LSF}_{l,T-1}^{(s)}(M,N) \end{bmatrix} \times \begin{bmatrix} \alpha_l \\ \beta_l \\ \gamma_l \end{bmatrix} = \begin{bmatrix} \mathrm{LSF}_{l,1}^{(s)}(1,1) \\ \vdots \\ \mathrm{LSF}_{l,T}^{(s)}(M,N) \end{bmatrix} \tag{2}$$

where the training set consists of the pristine lth LSFs of each signal across the whole $M \times N$ matrices in the training set and T is the total number of LSFs in the training set. The aforementioned system can be solved for least squares using QR decomposition. In principle, the LSFs of each of the four subframes could be estimated, however, since the first and the third subframes can be successfully estimated by means of interpolation of the adjacent ones, (1) is only applied to predict the second and the fourth subframes. The corresponding LSF spatial prediction residual can be vectorially quantized more coarsely than if direct quantization without prediction had been performed. If only one neighbor is available, e.g., on the top and left border of an EMG signal matrix (assuming raster scan ordering of the signals in the matrix), the prediction can still be performed along the corresponding direction; however, the corresponding optimal coefficients (either α_l or β_l) are, in general, different from the ones used when both neighbors are available and need to be learned accordingly by properly modifying (2). On the other hand, if online training is desired, the training set should be made of the reconstructed LSFs of previously coded data, so that the decoder can perform the same computation as described previously. The causal context used for prediction can span more spatial dimensions. The quantizers have to be trained offline so as to minimize the reconstruction error on a training set of multichannel signals; both full vector quantization and split matrix vector quantization can be employed depending on the desired complexity and the quantizer order. We experimentally found that 11 bits/frame would suffice for surface EMG signals and 13 bits/frame for EEG signals to achieve comparable performance to 38 bit/frame independent LSF quantization (see Section III).

C. Residual Spatial Prediction

After short-term prediction, the residual signal is vectorially quantized. However, the residual excitation may still exhibit some degree of correlation with the residual signals from adjacent channels. For example, surface EMG signals detected along the direction of the muscle fibers are delayed with respect to each other, but, otherwise, have a similar shape [23]. EEG signals are also correlated when detected in closely spaced locations due to the low-pass filtering effect of the volume conductor that limits spatial selectivity [24]. This correlation can be removed by means of prediction using the reconstruction vectors from the residual data of already coded signals in a causal neighborhood; as for LSF, the predictor coefficients can either be learned offline on a training set or adaptively on past coded data to maintain synchronization with the decoder. In the first case, the coefficients might be suboptimal on a specific signal, whereas in the second case, the computational complexity is increased at both the encoder and the decoder sides.

Moreover, because the signals in a multichannel recording are, in general, not temporally aligned, longer filters need to be employed, thus taking into consideration samples from a temporally local neighborhood of the current sample at the current time instant. Thus, given the STP residual excitation $\underline{R}_{(i,j)} = [r_{(i,j)}[0], r_{(i,j)}[1], \ldots, r_{(i,j)}[39]]$ of a generic single-channel signal at the spatial position (i, j), $(i,j) \in [2,W] \times [2,H]$ in a $W \times H$ multichannel recording, a prediction can be formed as

$$\hat{r}_{(i,j)}(t) = \sum_{k=-T1}^{T2} a_k \tilde{r}_{(i-1,j)}[t+k] + \sum_{k=-T1}^{T2} b_k \tilde{r}_{(i,j-1)}[t+k] \tag{3}$$

where a_k and b_k are the coefficients of a predictor weighting the portion of residual signals in the time interval $[t-T1, t+T2]$ from adjacent, already coded signals, and $\tilde{\underline{R}}_{(i,j)} = [\tilde{r}_{(i,j)}[0], \tilde{r}_{(i,j)}[1], \ldots, \tilde{r}_{(i,j)}[39]]$ is the decoder's reconstruction of the excitation signal at the position (i, j) for the current frame. As in the case of the LSF coefficients, more signals can be involved in forming the prediction, as long as they belong to a causal context of previous data so that the decoder can symmetrically perform the same computation without additional delay.

Finally, the prediction residual error $\underline{\mathbf{E}}_{(i,j)} = \underline{\mathbf{R}}_{(i,j)} - \hat{\underline{\mathbf{R}}}_{(i,j)}$ is quantized using an algebraic codebook and analysis-by-synthesis as in the standard ACELP algorithm; thus, seeking for a representation constituted by a number of unitary impulses and a gain aimed at minimizing the MSE of the overall reconstruction. The quantization index, indicating the location and the sign of the impulses, is then sent to the decoder along with the gain. The encoder performs its prediction exploiting information available at the decoder.

Using the described method, the compression ratio, defined as

$$C = \frac{L_{\mathrm{orig}} - L_{\mathrm{compressed}}}{L_{\mathrm{orig}}} \% \tag{4}$$

(where L_{orig} and $L_{\mathrm{compressed}}$ refer, respectively, to the pristine and compressed bitstream sizes), is fixed, given the rate of the quantizers. For example, for an EMG application, where each 160-sample and 12-bit/sample frame is encoded using 171 bits, the compression ratio is approximately 91%.

TABLE I
BIT ALLOCATION FOR VARIOUS PARAMETERS FOR AN 160-SAMPLE INPUT FRAME FOR INDEPENDENT ACELP CODING, SPECTRAL PREDICTION, AND PROPOSED TECHNIQUE

	Parameter	Bit per frame
Independent ACELP coding	LSF	38
	Algebraic codebook quantization index	140
	Algebraic codebook gain	20
	Total	**198**
ACELP coding exploiting redundancy of the spectra	LSF	11
	Algebraic codebook quantization index	140
	Algebraic codebook gain	20
	Total	**171**
Proposed technique	LSF	11
	Algebraic codebook quantization index	140
	Algebraic codebook gain	20
	Total	**171**

TABLE II
AVERAGE SNR FOR INDEPENDENT ACELP CODING, SPECTRAL PREDICTION ACELP CODING, AND PROPOSED TECHNIQUE FOR MULTICHANNEL EMG RECORDINGS

	SNR (dB)		
Signal	**Indep. Coding**	**Spectral prediction**	**Proposed technique**
Cg	15.25	15.19	17.63
Df	16.98	17.14	22.02
Em	15.72	15.68	18.93
Lm	14.75	14.69	18.06
Mg	13.54	13.39	14.68
Sm	16.45	16.42	19.78
Sr	16.41	16.37	21.62
Average	15.58	15.55	18.96

TABLE III
AVERAGE SNR FOR INDEPENDENT ACELP CODING, SPECTRAL PREDICTION ACELP CODING, AND THE PROPOSED TECHNIQUE FOR THE MULTICHANNEL EEG RECORDINGS

Signal	SNR (dB)		
	Indep. Coding	**Spectral prediction**	**Proposed technique**
EEG 1	19.70	19.52	22.24
EEG 2	19.73	19.49	22.23
EEG 3	19.84	19.86	22.20
EEG 4	19.61	19.71	21.88
EEG 5	19.89	19.83	22.19
Average	19.75	19.68	22.15

D. Signal Acquisition

The proposed algorithm was representatively tested on multichannel surface EMG and EEG signals. The surface EMG signals were detected from the dominant biceps brachii muscle of seven healthy men (mean age $\pm$ standard deviation: 27.7 $\pm$ 2.3 years) with a grid of 61 electrodes (diameter 1.27 mm; 5-mm interelectrode distance) arranged in 13 rows and five 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 of rest, the subject produced a contraction at 50% MVC lasting 20 s. The sampling frequency was 1 kHz, amplification gain 2000, bandwidth of the analog filters 10–400 Hz, and 12 bits/sample.

EEG signals were recorded using the standard 10–20 electrode placement with 15 tin electrodes (Electrocap, USA) at locations FC3, FC1, FCz, FC2, FC4, C3, C1, C7, C2, C4, CP3, CP1, CPz, CP2, and CP4. The signals were recorded from five healthy men (mean age $\pm$ SD: 31.2 $\pm$ 3.6 years) during isometric ankle dorsiflexions at 5% of the maximal force, and were amplified with a 128-channel digital full-band dc EEG amplifier (Ant Management (Netherlands) B.V., The Netherlands) in monopolar mode with reference to the electrode M1 (right mastoid). The sampling frequency was 2048 Hz, amplification gain 20, bandwidth of the analog filters 0–553 Hz, and 12 bits/sample.

E. Signal Analysis

The average SNR in signal reconstruction was used as distortion metrics

$$\mathrm{SNR} = 10 \log \left(\frac{\sum_{i,j} \sum_{t=1}^{N} s_{(i,j)}^2[t]}{\sum_{i,j} \sum_{t=1}^{N} \left(s_{(i,j)}[t] - \hat{s}_{(i,j)}[t] \right)^2} \right) \text{ dB}. \tag{5}$$

The SNR is a widely accepted objective performance measure and provides a global indication of the average quality of multichannel signal reconstruction. Although different indexes might be adopted for specific applications, the SNR is sufficiently general to objectively compare the performance of different coding methods without being limited to a specific application.

Two training sets, consisting of three multichannel EMG recordings and three multichannel EEG recordings from three subjects not considered for the test set, were used to separately learn the optimal predictors and quantizers for the two representative applications. Training was then performed offline to learn the coefficients and quantizers to be used on the test sets; thus, the training time did not affect the coding time. After training, each multichannel recording in the test set was compressed

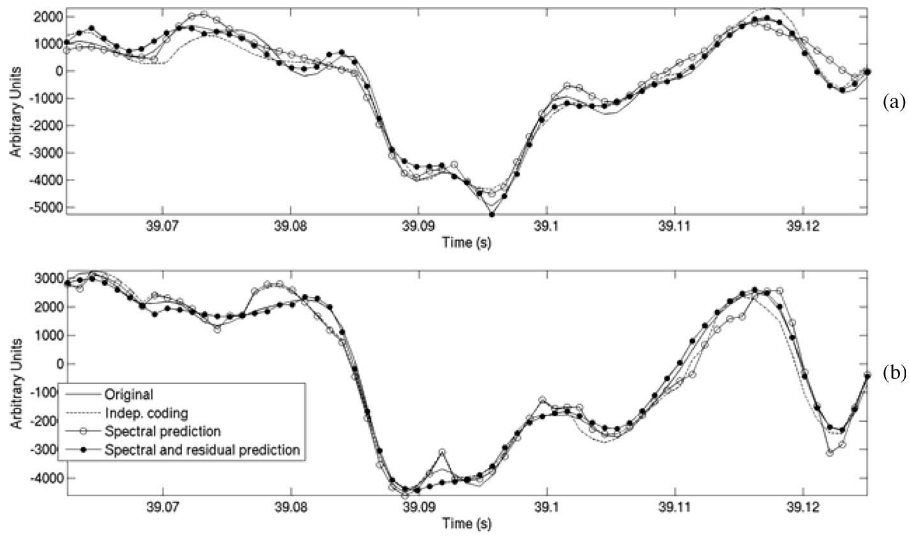

Fig. 2. Portion of two adjacent EMG signals from the same multichannel recording. The original signal, and the reconstruction from independent coding, spectral prediction, and the proposed technique are depicted. Compression ratio for independent coding was set to 89.6%, whereas 91% was set for both spectral prediction and the proposed technique.

using three techniques. For both applications, the training and the test sets did not share any information and were constituted by signals belonging to different subjects, i.e., the coefficients and quantizers learned were not specific to a subject. First, independent ACELP coding of each signal was performed as previously described in [7]. Second, correlation of the spectra across the signal matrices (referred to as spectral prediction in the following) was exploited according to (1), and the bit rate was set in order to match the performance (in terms of SNR) of independent coding. Lastly, the proposed technique, which combines spatial prediction of the residual data and the spectral prediction, was tested at the same bit rate as for spectral prediction, in order to assess the gain in terms of SNR, using $T1 = T2 = 3$ samples [see (3)].

III. Results

Table I shows the bit allocation of the encoded bitstream for the frames of 160 samples used for surface EMG coding. A similar bit allocation was used for the EEG recordings, but 13 bits, instead of 11, were used for the LSFs in order to match the performance of 38-bit quantization used for independent ACELP coding. With the bit allocation of Table I, the compression ratio for independent coding was 89.6%, while for spectral prediction and the proposed technique using spatial information, the compression ratio was 91%. Compression ratio can be changed by changing the rate of the quantizers, which also means that training has to be performed again to learn the optimal quantizers and coefficients for the new target bit rate. Spectral prediction was tuned to match the performance (in terms of SNR) of independent coding.

Table II reports the SNR [see (5)] for the multichannel EMG recordings with respect to the original, uncoded signal for the three techniques. The results refer to the average SNRs in the reconstruction, as measured over the entire detection grid. The average gain of the proposed technique with respect to independent coding of each channel was 3.4 ± 1.3 dB with a compression ratio of 91% (proposed method) versus 89.6% (independent coding). Table III shows the corresponding results for the EEG recordings, for which the gain with respect to individual channel coding was 2.4 ± 0.1 dB.

Figs. 2 and 3 show portions of multichannel EMG and EEG recordings, respectively, and the corresponding reconstruction for the three techniques.

IV. Discussion

A model-based lossy compression technique for multidimensional biomedical signals was proposed, exploiting both temporal and spatial redundancy in a set of biomedical signals. Biomedical signals are usually characterized by strong correlation along the time axis and can often be considered WSS for relatively long epochs (up to 1–2 s), thus being amenable to compression using codebook-based techniques. In addition, signals from spatially related channels in a multichannel biomedical recording have strong correlation being often characterized mostly by subtle changes in the power spectra and delays between the channels due, for example, to source propagation. Thus, these signals differ from other types of multidimensional signals, such as video sequences, where the signal cannot usually be considered WSS for long periods of time. Spatial redundancy in biomedical recordings is not only determined by the electrode spacing, for example, the selectivity of the recording system at each detection site also affects spatial correlation. In the cases analyzed, the EEG signals were recorded with respect to reference electrodes at the ear lobes (monopolar recordings), whereas the EMG was recorded with the more selective bipolar system. Moreover, the volume conductor also influences spatial redundancy.

Exploiting the spatial redundancy of the spectra of spatially adjacent signals yields a significant reduction in the number of bits needed to faithfully represent the LSF coefficients. Up to

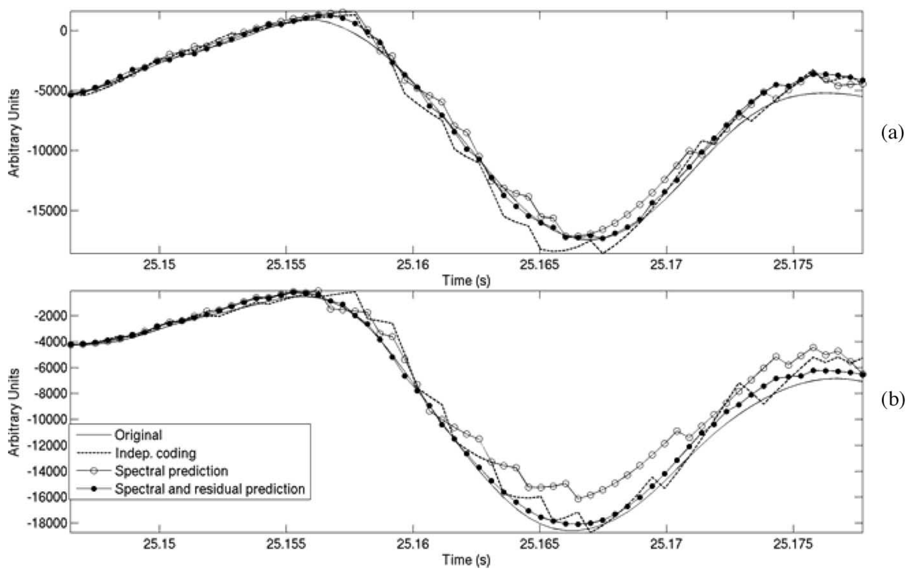

Fig. 3. Portion of two adjacent EEG signals from the same multichannel recording. The original signal, and the reconstruction from independent coding, spectral prediction, and the proposed technique are depicted. Compression ratio for independent coding is set to 89.6%, whereas 91% was set for both spectral prediction and the proposed technique.

71% fewer bits were needed to code the LSF coefficients with respect to independent ACELP coding where they constituted approximately 20% of the compressed bitstream whose length is, however, still largely due to the residual quantization indexes. However, significant correlation across the residual signals in the matrix is still present, and can be exploited to better reconstruct the waveforms. The proposed technique achieved a higher compression ratio than independent ACELP coding with improved quality of the reconstruction. The improvement in SNR obtained in the two representative applications ($\sim$3 dB) is significant (see Figs. 2 and 3), especially for methods that aim at the extraction of information on individual signal sources. For example, surface EMG signals can be decomposed into individual motor unit activities and the decomposition is based on the shape of the motor unit action potentials [25]. Low distortion of motor unit action potential shapes is, thus, fundamental for robust decomposition. However, it has to be noted that none of the assumptions of the proposed method is specific for the representative applications investigated in this study (EMG or EEG). The main aim was the proposal and test of a general method for compression of multichannel biomedical signals. The significance of improvement over previous methods should be discussed in relation to specific applications.

Although the proposed technique was tested offline, once the coefficients have been learned, the method can also run online. However, both complexity and algorithmic delay grow linearly with the number of channels to be processed that, depending on processing power or power constraints, may pose a limit on the total number of channels. On the other hand, the proposed technique builds on the ACELP paradigm, which is known to require approximately 14 million instructions/s (MIPS) [26] to run at eight times the rate of a single-channel EMG or EEG signal (narrow-band speech is usually sampled at 8 KHz), which can, therefore, be taken as the rough estimate of the processing power needed to encode eight channels.

V. Conclusion

In this paper, we proposed a model-based compression method for multidimensional biomedical signals. Each signal is modeled by means of a filter and a residual error that are appropriately quantized and sent to the decoder. The method exploits both intra- and interchannel redundancy (in time and space, respectively) to achieve high compression ratio, while yielding better performance in terms of quality of the reconstruction for a given bit rate (up to $\sim$3.4 dB for the EMG application and $\sim$2.4 dB for the EEG application) with respect to competing methods exploiting only temporal or spectral redundancies without any significant complexity increase with respect to single-channel coding.

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