Biomedical Signal Processing and Control 31 (2017) 295–300

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Efficient lossless multi-channel EEG compression based on channel clustering

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ARTICLE INFO

Article history:
Received 19 December 2015
Received in revised form 25 August 2016
Accepted 25 August 2016

Keywords:
Lossless compression
Channel clustering
EEG signals
Telemedicine
DPCM

ABSTRACT

With the growth of telemedicine systems, transferring a large number of medical signals such as for an EEG is a critical challenge. Intelligent analyzing systems, responsible for analyzing medical signals, are a very important part of any telemedicine system. These systems need data with high quality in order to detect abnormal events and diseases. Lossless compression methods play an important role when coding medical signals for telemedicine systems since the data remains unchanged. Multi-channel EEG signals for medical applications are usually acquired by a number of electrodes placed on different parts of the scalp. According to electrode placements, it is necessary to take into account their multi-channel structure to propose efficient compression methods. This paper uses inter-channel and intra-channel correlations to propose an efficient and simple lossless compression method. In the first stage, a differential pulse code modulation technique is used as a preprocessing step for extracting intra-channel correlation. Subsequently, channels are grouped in different clusters, and the centroid of each cluster is calculated and coded by arithmetic coding. In the second stage, the difference between the centroid and the data of channels in each cluster is calculated and compressed by arithmetic coding. The proposed method is capable of lossless EEG signal compression with a higher compression rate than existing methods.

1. Introduction

Electroencephalogram (EEG) demonstrates the electrical activities of the brain by one-dimensional signals gathered by electrodes placed on the scalp. Therefore, EEG signals contain information that is very important for researchers and physicians. Brain signals are commonly used in brain computer interface (BCI), and they are also utilized in detecting different mental states and diseases in telemedicine systems. EEG signals are interpreted and analyzed in two ways [1]: 1) by humans, and 2) by automatic intelligent systems. Humans are capable of analyzing EEG signals accurately; however, the analysis is very difficult and time consuming. Therefore, it is essential to use intelligent analyzing systems. In order to increase the accuracy of these systems, medical data that is as close as possible to being error-free is needed [2]. Intelligent systems are usually parts of remote telemedicine, where the data can be remotely transferred from the person's mobile phone to any destination, such as a remote terminal in a hospital [3,4]. Also, the need for continuous care increases the amount of data transferred through communication channels. This data requires fast and lossless transmissions, which highlights the role of lossless compression. Although lossy compression provides an appropriate compression rate, intelligent systems need data without degradation to correctly detect abnormal events and diseases.

Data compression methods are generally divided into lossless and lossy. In lossless methods, the reconstructed data is the same as the original data without any error or change. These methods do not possess high compression rates. Therefore, lossy methods are used to increase the compression rate. Since a part of the data is removed in lossy methods, the reconstructed data will be different from the original one. A near-lossless method can be achieved by applying a condition on maximum error to guarantee that the reconstructed error value is less than a specific value [5].

Lossless compression methods for EEG can be divided into two groups: single stage methods and multi-stage methods. Single stage methods only require applying entropy reduction techniques, e.g., Hoffman or Arithmetic, on the original data [6]. Multistage methods use preprocessing techniques before entropy reduction. These preprocessing techniques include dependency removal by correlation dimension [7], removing bias values by backward difference [8–10], and arranging channels in a (two-dimensional) matrix or (three-dimensional) volume [8–10]. Then, in the next stages, artificial neural networks [7,11,12] or different transforms,

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http://dx.doi.org/10.1016/j.bspc.2016.08.024
1746-8094/

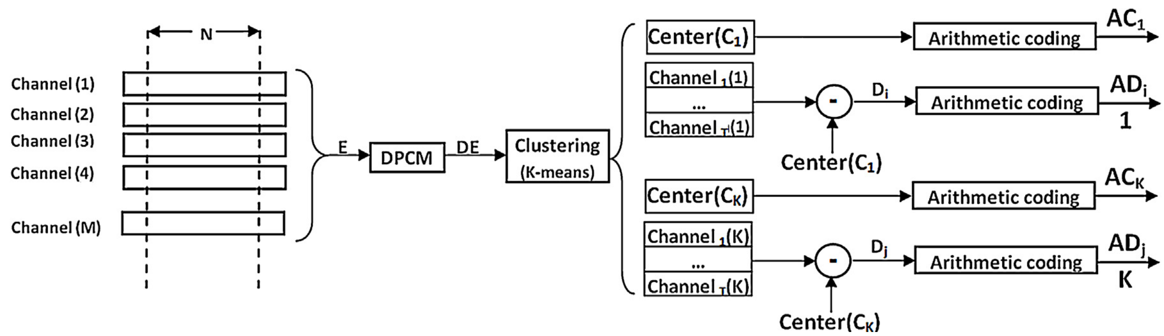

Fig. 1. Proposed channel clustering compression algorithm.

such as wavelet [8,9], Karhunen–Loève transform (KLT) and discrete cosine transform (DCT) [10], or frequency filters [13] are used to remove more redundancy. Finally, entropy reduction techniques are applied [14].

Near-lossless methods are based on transforms [1,5] or predictors [15,16], where the data is first coded into transforms or predictors and then transmitted with loss. Next, errors are compressed by applying a maximum error condition and entropy reduction methods.

In order to achieve a high compression rate, lossy methods attempt to remove a part of the original data which causes errors in the reconstructed data. Most lossy methods are based on transformation, especially wavelet transform [4,17–22]. Most techniques apply quantization and thresholding to the original data or coefficients to reduce the data size. Also, there are some other EEG compression approaches based on dictionary [23], fractals [24], genetic algorithms [24,25], compressed sensing [3,26], and Diolp fitting [27].

This paper aims to remove intra-channel and inter-channel dependencies efficiently. In the first stage, the differential pulse code modulation (DPCM) method is employed to reduce the intra-channel redundancy and to extract appropriate data with a smaller range than the original data. This stage prepares the data for clustering and for the arithmetic coding stage since data with smaller range increases the clustering accuracy and arithmetic compression rate. In the second stage, similar channels are grouped using clustering algorithms to remove inter-channel dependencies. The centroid of each group is determined and coded by using an entropy reduction technique. The difference between each channel's data with its corresponding cluster's centroid is calculated and coded by arithmetic entropy reduction.

This paper is organized as follows: Section 2 explains a multi-channel lossless method based on clustering, Section 3 demonstrates experimental results, and Section 4 presents conclusions.

2. Proposed method

The proposed method aims to extract the correlations that exist in each channel and between channels in two stages. First, the time-domain data of all channels are divided into N symbol blocks. As mentioned, EEG signals have intra-channel dependencies, which have been studied in previous research. Therefore, in the first stage, using DPCM, redundant data is extracted from each block, which reduces the range of data. Since most of the data in neighbor electrodes (or channels) are highly dependent, there are redundant data in multiple channels that can be eliminated. In the second stage, using a novel approach, the data blocks of different channels are first clustered to specify correlated channels. Subsequently, the centroid of each cluster is calculated in order to remove existing correlation in the blocks of each cluster. Finally, the values of the clusters' centroids, as well as the difference of each channel with its cluster centroid (which is much smaller than the original data), are compressed using arithmetic coding. The overall structure of the proposed method is presented in Fig. 1.

In the proposed method, the bias values and dependencies of the data in each channel are removed using the DPCM technique. DPCM is a procedure for removing spatial redundancy or intra-channel coding. The basic concept of DPCM is based on the fact that the correlation between successive samples in natural signals is high, and by employing the difference between current and previous samples, this redundancy can be significantly removed. DPCM code words represent the difference between samples to produce uncorrelated samples, as given by:

$$y_n = x_n - x_{n-1} \tag{1}$$

where y_n is the uncorrelated data which is calculated by the difference between the current sample, x_n, and the previous one, x_{n-1}. This method is one of the most significant approaches in lossless compression. DPCM is more efficient than methods such as IntDCT or IntKLT [10]. DPCM not only removes the intra-channel redundancy, but also increases the similarity of different channels in each cluster by removing the bias values as shown in Fig. 2a and b.

Also, to eliminate redundancies in adjacent channels of EEG with a multi-channel structure, it is essential to find the dependent channels since the data of adjacent channels are always highly correlated [1,5]. Therefore, inter-channel redundancies of each group can be eliminated by finding an appropriate cluster centroid among similar channels. Selecting an appropriate centroid plays an important role in removing inter-channel correlation. Thus, the well-known KMEANS algorithm is employed to cluster all the channels in different K groups and calculate the centroid of each cluster:

$$DE = DPCM\,(E) \tag{2}$$

$$C = Kmeans\,(DE, K) \tag{3}$$

Where DE is the output resulting from applying DPCM on all channels, and C is the centroid of K clusters. The data corresponding to the clusters' centroids are rounded and sent using arithmetic coding. Subsequently, the difference between each channel and the corresponding cluster's centroid is calculated. These differences are compressed using arithmetic coding and sent along with the index of the corresponding cluster centroid. The results of these steps are shown in Fig. 2.

$$D_i = \mathrm{DE}_i - C_k \quad \left(\text{where channel} i \in k^{th}\text{cluster}\right) \tag{4}$$

$$AD_i = Aritmetic\,(D_i) \tag{5}$$

$$SendData = (AD_i, k) \tag{6}$$

At the receiver, cluster-centroid-difference data of each channel is reconstructed by inverse Arithmetic coding.

$$ReciveData = (AD_i, k) \tag{7}$$