Mr. Nikhil V. Raut, Prof. Ritu Chauhan / International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com
Vol. 2, Issue4, July-August 2012, pp.2233-2236

Neural Signal Compression With Multiwavelet Transform Using Video Compression Techniques

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ABSTRACT

In the field of biomedical engineering Multichannel neural recording is one of the most important topics. This is because there is a need to considerably reduce large amounts of data without degrading the data quality for easy transfer through wireless transmission. Video compression technology is of considerable importance in the field of signal processing. There are many similarities between multichannel neural signals and video signals. So advanced video compression algorithm can be implemented to compress neural signal. In this study, we propose a signal compression method using multiwavelet transform, vector quantization that employs motion estimation/compensation to reduce the redundancy between successive neural video frames.

Keywords -Multichannel evoked neural signals; biomedical signal processing; video signal processing; multiwavelet transform; vector quantization.

I. INTRODUCTION

Recently, in the field of biomedical engineering, neural data recording has gained considerable importance especially by employing neuro prosthetic devices and brain-machine interfaces (BMIs)[2]. Neuro means brain; therefore, 'neuro-signal' refers to a signal related to the brain. A common approach to obtaining neuro-signal information is an Electroencephalograph (EEG), which is a method of measuring and recording neuro-signals using electrodes placed on the scalp. Furthermore, multichannel neural recording is commonly used and is necessary for bioanalysis. However, recording large amounts of data has been a challenging task. In this experiment the recorded neural signal is used for further processing shown in fig. 1.Before proceeding with signal processing, we shall modify the neural signal by employing a transform. This is because that the numerical range of neural signals differs from that of video signals. However, the precision of both signals is similar—8 bits[3]. We transform the neural signal by using multiwavelet transform so that the video compression algorithm can be applied to it.

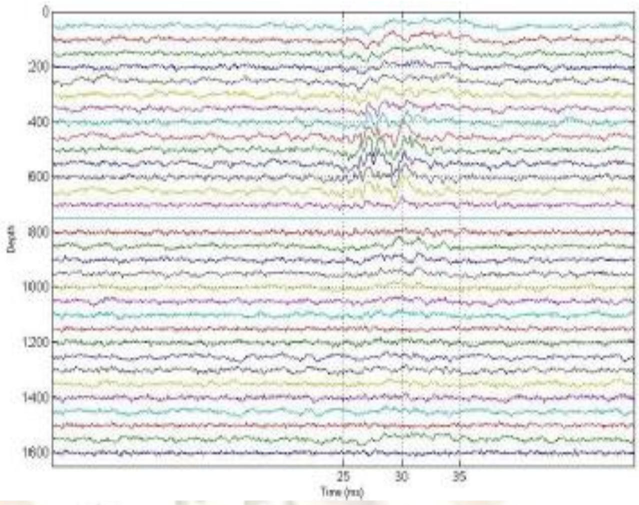

Fig 1: Multichannel Neural Signal used in the experiment

This high correlation indicates high spatial redundancy in the multichannel neural signal. Once the neuron fires, similar spike signals are detected by more than one electrode as shown in table I. Video signals have the same characteristic. A series of images comprise the video, but neighbor images do not change significantly. Recently video compression algorithm has many skills to deal with it. That is way we choose video compression algorithm to compress multichannel neural signal [1]. The values of neighboring electrodes with the correlation are shown in Table I [4].

Table I: Correlation between neighboring electrodes

Channel	1&2	2&3	3&4	4&5	5&6
Correlation	0.893	0.869	0.920	0.898	0.847
Channel	6&7	7&8	8&9	9&10	10&11
Correlation	0.856	0.849	0.124	0.610	0.841
Channel	11&12	12&13	13&14	14&15	15&16
Correlation	0.889	0.944	0.583	0.762	0.722

II. HOW VIDEO COMPRESSION ALGORITHM WORKS? :

1.1 Multiwavelet Transform

The spatial redundancy which is present between the image pixels can be reduced by taking transforms which decorrelates the similarities among the pixels. The choice of the transforms depends upon a number of factors, in particular, computational complexity and coding gain. Coding gain is a measure of how well the transformation compacts the energy into a small number of coefficients. The predicted error frames are usually encoded using either block-based transforms, such as DCT, or non-block-based coding, such as subband coding or the wavelet transform. A major problem with a block-based transform coding algorithm is the existence of the visually unpleasant block artifacts, especially at low data rates. This problem is eliminated using wavelet transform, which is usually applied over the entire image. The wavelet transform has been used in video coding for the compression of motion predicted error frames [6].

Wavelet transform decomposes the recorded signal in both time and frequency domain which turns out to be very useful in feature extraction [5]. It generates a set of coefficients corresponding to the low-frequency components, called the approximations" and another set of coefficients corresponding to the high frequency components, called the "details", while preserving the timing information. If we consider only the approximations for reconstructing the neural signal by using an inverse wavelet transform, then we achieve our first level of data compression, along with de-noising. Multiwavelets can be considered as generalization of scalar wavelets. Scalar wavelets have a single scaling function φ(t) and wavelet function ψ(t) . Multiwavelets have two or more scaling and wavelet functions.

$$\varphi(t) = \sqrt{2}\sum_{-\infty}^{\infty} HK \ \varphi(2t-k) \qquad (1)$$

$$\psi(t) = \sqrt{2}\sum_{-\infty}^{\infty} GK \ \varphi(2t-k) \qquad (2)$$

where, $\{H_K\}$ and $\{G_K\}$ are 2 x 2 matrix filters defined as

$$H_K = \begin{bmatrix} h0\,(2k) & h0\,(2k+1) \\ h1\,(2k) & h1\,(2k+1) \end{bmatrix} \qquad (3)$$

$$G_K = \begin{bmatrix} g0\,(2k) & g0\,(2k+1) \\ g1\,(2k) & g1\,(2k+1) \end{bmatrix} \qquad (4)$$

where $\{h_k(n)\}$and $\{g_k(n)\}$are the scaling and wavelet filter sequences such that $\sum_n h^2(n) = 1$ and $\sum_n g^2(n)=1$.The matrix elements in the filter given in equations 3 and 4 provide more degrees of freedom than a traditional scalar wavelet. Due to these extra degrees of freedom, multiwavelets can simultaneously achieve orthogonality, symmetry and high order of approximation [6].

1.2 Vector Quantization:

VQ collects the transformation coefficients into blocks and assigns one symbol to each block. VQ is a powerful tool for data compression. Vector quantization extends scalar quantization to higher dimensional space. The superiority of VQ lies in the block coding gain, the flexibility in partitioning the vector space, and the ability to exploit intra-vector correlations. VQ is an error refinement scheme in which inputs to a stage are residual vectors from the previous stage and they tend to be less and less correlated as the process proceeds. VQ is a non uniform vector quantizer, which exploits the correlation between vector components and allocates quantization centroids in accordance with the probability distribution density. The encoder for this VQ simply transmits a pair of indices specifying the selected codewords for each stage and the task of the decoder is to perform two table look ups to generate and then sum the two codewords [7].

1.3 Motion Estimation and Compensation

The main objective of any motion estimation algorithm is to exploit the strong frame to frame correlation along the temporal dimension. The references between the different types of frames are realized by a process called motion estimation or motion compensation. The resulting frame correlation, and therefore the pixel arithmetic difference, strongly depends on how good the motion estimation algorithm is implemented. In video compression algorithms, Motion Estimation and Compensation using motion vector play an important role in providing a high compression rate.

The main objective of any motion estimation algorithm is to exploit the strong frame to frame correlation along the temporal dimension. Motion estimation examines the movement of objects in an image sequence to obtain vectors representing the estimated motion. Motion is described by a two-dimensional vector, known as motion vector (MV) that specifies where to retrieve a macro-block from the reference frames. The motion vector can be found using matching criterion. The MV helps to reduce spatial redundancy. Thus, we can determine the MV between successive frames [1] [7]. In this case, we determine only the MVs between frames and their differences and do not re-record the amount of the data. Thus, spatial redundancy is eliminated and the data size can be decreased considerably.

III. PROPOSED ALGORITHM:

The commonly used video compression algorithms such as H.264, scalable video compression (SVC), and multiview compression are very complex. However, a complex algorithm shows better performance than a simple algorithm, albeit at a high computational cost. In Fig. 2, we present the block diagram of the proposed algorithm. In order to apply video compression to multichannel neural signals, it is necessary to generate a “neural video sequence.” For analyzing the method of generation of a neural video sequence, it is necessary to know the operation of the video compression algorithm in order to remove the spatial redundancy.

The block diagram of the proposed scheme is shown in Figure 2. A trial comprises 50 frames; we consider the frames of a trial as a single group. We use the previous frame to determine the MV of a frame, and then perform video compression block diagram (Fig. 2), motion estimation, and motion compensation. After wavelet transformation (Multiwavelet) of the residue, vector quantization is performed. From the Figure, it is clear that multiwavelet transform is taken for the input frame; the resultant coefficients are grouped into vectors. The vectors are mapped into one of the code vectors. The number of code vectors in the codebook is decided by rate and dimension.

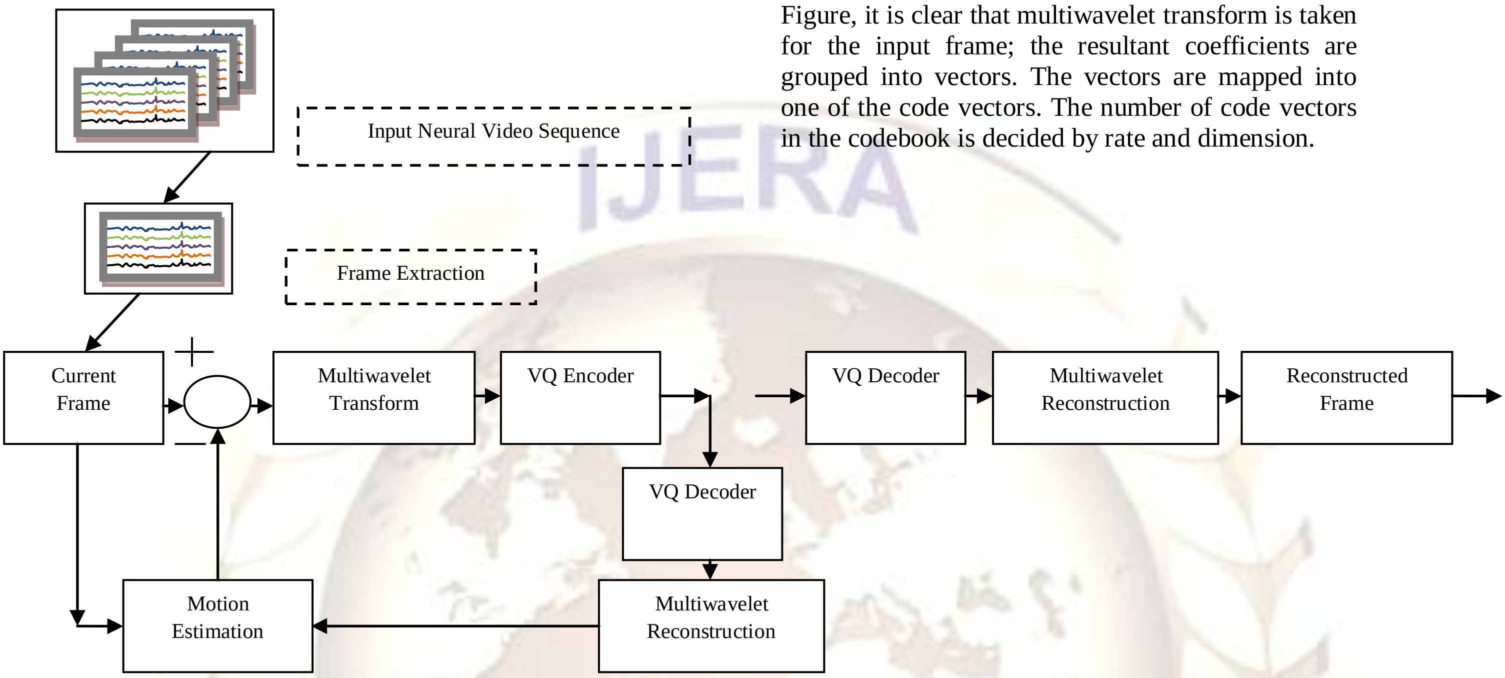

Fig 2. Block Diagram of Neural Signal Compression

IV. RESULTS AND DISCUSSION:

To evaluate the performance of the proposed scheme, the peak signal to noise ratio (PSNR) based on mean square error is used as a quality measure, and its value can be determined by the following equation

$$PSNR = 10 \log_{10}\left(\frac{255^2}{\frac{1}{N}\sum(P_{ref}(x,y)-P_{prc}(x,y))^2}\right)$$

Where N the total is number of pixels within the image, Pref (x, y) and Pprc (x, y) are the pixel values of the reference and the processed images respectively. The summation of PSNR, over the image frames, will then be divided by the total number of frames to obtain the average value. The performance of the proposed scheme is compared with wavelet based scheme using the average PSNR value over fifty frames obtained from the experiment. The performance of the proposed scheme is obtained using wavelet based scheme using the average PSNR value over fifty frames and from the experiment value of PSNR is obtained as mentioned in the table. Using multiwavelet transform and vector quantization the compression ratio 5.60 is achieved

Table II: Results of Neural Video Sequence

Neural Video Frame	PSNR(dB)
Frame 1	26.09
Frame 25	25.88
Frame 50	27.65
Frame 75	26.47

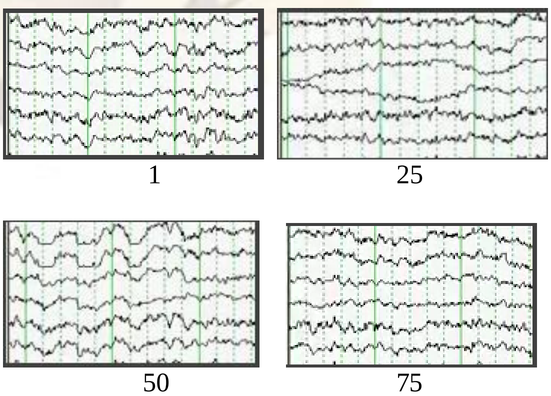

Fig 3: 1, 25, 50, 75th frames from neural Video sequence.

The proposed algorithm is compared with DCT based quantization scheme, the parameters taken into consideration are compression ratio and average PSNR, the results are given in Table III.

Table III: Comparison of Multiwavelet and DCT results

Transform	Average PSNR (dB)	Compression Ratio
Multiwavelet	29.47	5.60
DCT	26.45	4.12

From Table III, the results of DCT are obtained for the neural video sequence shown in Fig. 3 and these results are compared with Multiwavelet transform.

V. CONCLUSION:

In biomedical engineering Neural signal processing will undoubtedly have wide applications in future. The computation complexity of the algorithm, along with the compressed data rate, and the visual quality of the decoded video are the three major factors used to evaluate a video compression algorithm. An ideal algorithm should have a low computation complexity, a low compressed data rate and a high visual quality for the decoded video. However, these three factors cannot be achieved simultaneously. The computation complexity directly affects the time needed to compress a video sequence. Hence the proposed video compression algorithm is implemented with multiwavelet as the transform, vector quantization as the quantization scheme. In this study, we use a video compression algorithm for multichannel neural signal processing.

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