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Neural Signal Compression Using Video Compression Techniques

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Abstract- **In the biomedical engineering Multichannel neural recording is one of the most important topics. Without degrading the quality the large amount of data is to be easily transfer through wireless transmission. For neural data reduction there are so many techniques that follow different factors. In the field of signal processing Video compression technology is of considerable importance. The paper describes a new approach to the video compression problem. Our method uses the neural network image compression algorithm which is based on the vector quantization (VQ). In this method of image compression two different neural network structures are exploited in the following elements of the proposed system: In order to improve performance of the algorithm a competitive neural networks quantized and a neuronal predictor for the image compression based on this approach it is important to correctly detect scene changes.**

Keywords **-Multichannel evoked neural signals; biomedicalsignal 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 neuroprosthetic devices and brain-machine interfaces (BMIs).we know that Neuro is the brain; therefore, ‗neuro-signal' refers to a signal associated to the brain. A common approachto obtaining neuro-signal Information is an Electro encephalo graph (EEG), which is a method of measuring and recording neuro-signals using electrodes placed on the scalp, so the multichannel neural recording is commonly used and is necessary for bioanalysis. To recording large amounts of data is a challenging task. In this experiment the neural signal is recorded for further processing shown in fig. 1.Before signal processing, we shall modify the neural signal by employing a transform. For this reason the numerical range of neural signals differs from that of video signals. However, the both signals have the similar precision is similar—8 bits [3]. By using multiwavelet transform We transform the neural signal The video compression algorithm can be applied to it.

II. VIDEO COMPRESSION ALGORITHM:

The design of the compression algorithm described here is based on the existing algorithm described in [9–11]. Selected algorithm due to neural network features presents better adjustment to a frame and gives better compression. The extension includes a scene change detection algorithm, which is based on the correlation between frames. The diagram below Fig shows the proposed algorithm. Fig. 1. Video compression algorithm 2.1 Neuronal Image Compression Algorithm In the literature several methods for image compression have been proposed. Among them the vector quantization (VQ) technique has emerged as an effective tool in this area of research [12]. A special approach to image compression combines the VQ technique with traditional (scalar) differential pulse code modulation (DPCM) leading to the predictive vector quantization (PVQ). In this paper, we develop a methodology where the vector quantizer will be based on competitive neural network, whereas the predictor will be designed as the nonlinear neural network. We assume that an image is represented by an N1 × N2 array of pixels X = [xn1,n2]; n1 = 1,2,...,N1, n2 = 1,2,...,N2. The image is portioned into contiguous small blocks Y(k1,k2)=[ym1,m2 (k1,k2)] of the dimension M1 × M2; m1 = 1,2,...,M1, m2 = 1,2, ...,M2:

III. HOW VIDEO COMPRESSION ALGORITHM WORKS? :

A. Multiwavelet Transform

The spatial redundancy which is present between the image pixels can be reduced by taking transforms which correlates the similarities among the pixels. The selection 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 frequently encoded using either block-based transforms, such as DCT, or non-blockbased coding, such as Subband coding or the wavelet transform. A foremost problem with a block-based transform coding algorithm is the existence of the visually unpleasant block artifacts, especially at low data rates. This crisis is eliminated using wavelet transform, which is usually applied over the entire image. Thus the wavelet transform has been used in video coding for the compression of motion predicted error frames. The wavelet transform is a newly developed mathematical tool that provides a non-uniform division of data or signal, into different frequency components, and then studies each component with a resolution matched to its scale (Huang, 1999).In the analysis of transient signals because of its ability to extract both time and frequency information simultaneously, from such signals. Multiwavelets can be considered as simplification of scalar wavelets. Scalar wavelets have a single scaling function $\varphi(t)$ and waveletfunction$\psi(t)$. Multiwavelets have two or more scalingand wavelet functions.

$\varphi(t) = \varphi(2t-k)$(1)
$\psi(t) = \varphi(2t-k)$(2)

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

$$H_K = \begin{bmatrix} h0\ (2k) \\ h1\ (2k) \end{bmatrix} \quad (3)$$

$$G_K = \begin{bmatrix} g0\ (2k) \\ g1\ (2k) \end{bmatrix} \quad (4)$$

where $\{h_k(n)\}$and $\{g_k(n)\}$are the scaling and wavelet filter sequences. The matrix essentials in the filter given in equations 3 and 4 provide more degrees of freedom than a traditional scalar wavelet. Due to these spare degrees of freedom, multiwavelets can simultaneously achieve orthogonality, symmetry and high order of approximation [6].

B. Vector Quantization:

Vector quantization techqunic is a signal processing that allows the modeling of probability density functions by the distribution of prototype vectors. It was originally used for data compression. It's workings is by dividing a large set of points (vectors) into groups having approximately the same number of points closest to them. Each cluster is represented by its centroid point, The k-means and some other clustering algorithms. The concentration matching property of vector quantization is powerful, especially for identifying the density of large and high-dimensional data. while data points are represented by the index of their closest centroid, commonly occurring data have low error, and rare data high error. For this VQ is suitable for lossy data compression. It is also used for lossy data correction and density estimation. Vector quantization is built on the competitive learning paradigm, so it is closely related to the selforganizing map model and to sparse coding models used in deep learning algorithms such as auto encoder.

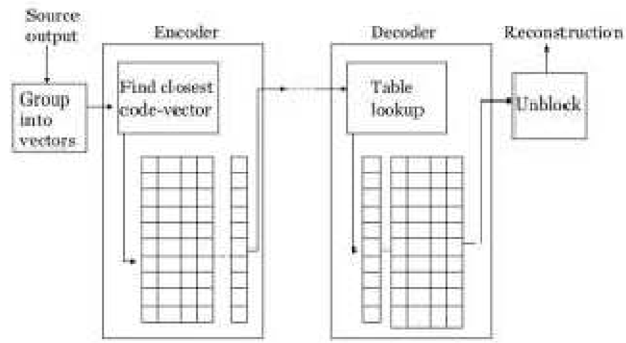
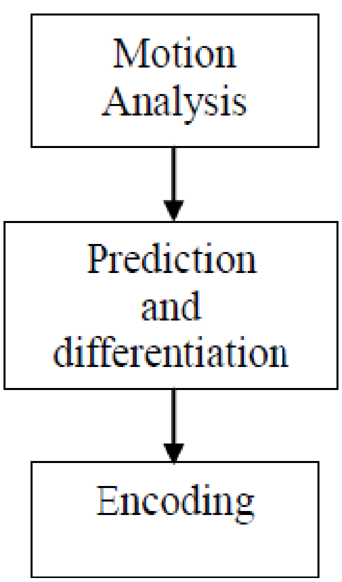


Fig. 1: Basic VQ Procedure

C. Motion Estimation and Compensation

In video compression algorithms, Motion Estimation and Compensation using motion vector show an important role in providing a high compression rate. The main impartial of any motion estimation algorithm is to exploit the strong frame to frame correlation along the temporal dimension. Motion estimation surveys the movement of objects in an image sequence to obtain vectors representing the estimated motion. The mixture of the motion estimation and motion compensation is a key part of the video coding. There are many methods to achieve ME/MC. The flow of Motion Estimation is given in fig

Fig. 2: Flow of Motion Estimation



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 originate using matching criterion. The MV helps to reduce spatial redundancy. Thus, we can determine the MV between successive frames [1][7]. In this container, we determine only the MVs between frames and their differences and do not re-record the amount of the data. Thus, spatial redundancy is excluded and the data size can be decreased considerably.

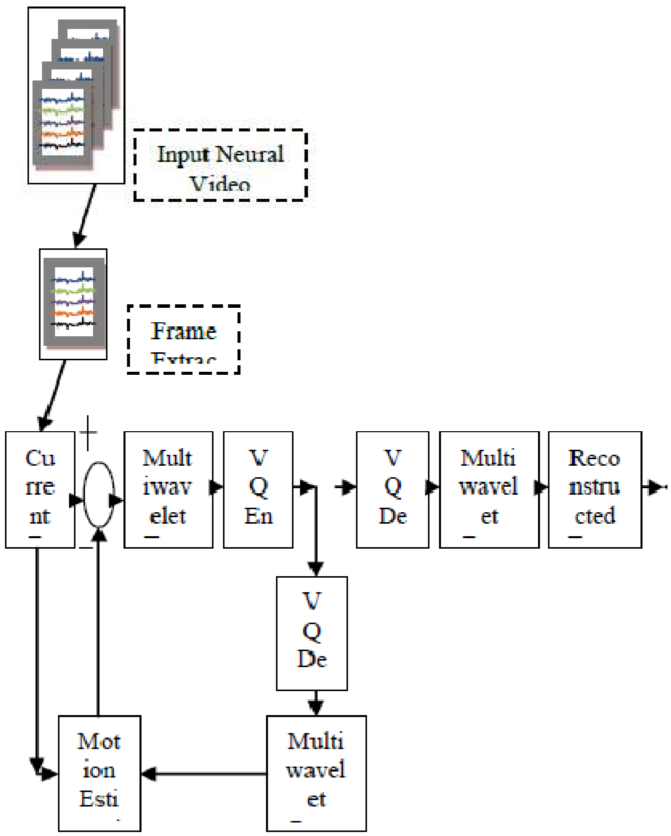


Fig. 4: Block Diagram of Neural Signal Compression

IV. PROPOSED ALGORITHM:

The commonly used video compression algorithms such as H.264, scalable video compression VC), and multiview ompression are very complex. However, a multifaceted algorithm shows better performance than a simple algorithm, albeit at a high computational cost. In Fig. 4, 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 needed 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 4. A trial comprises 50 frames, we consider the frames of a trial as a single group. We custom the previous frame to determine the MV of a frame, and then perform video compression block diagram (Fig. 4), motion estimation, and motion compensation. Afterward wavelet transformation (Multiwavelet) of the residue, vector quantization is performed. After the Figure, it is pure 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 code book is decided by rate and dimension.

V. RESULTS AND DISCUSSION:

To estimate 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

$$PSNR = 10 \log_{10} \left(\frac{1}{N} \Sigma (P_r \right.$$

Where N, the total is amount 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 summary 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 number of frames obtained from the experiment. The presentation of the proposed scheme is obtained using wavelet based scheme using the average PSNR. The PSNR values for different frames is shown in above table I. The 1 and 33th reconstructed frames are shown in fig.4.

VI. CONCLUSION:

In biomedical engineering Neural signal processing will unquestionably have wide applications in future. The estimation 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 alow estimation 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 suggested video compression algorithm is implemented with multiwavelet as the transform, vector quantization at the same time as the quantization scheme. In this learning, we use a video compression algorithm for multichannel neural signal processing

Table 1:. Results of Neural video sequence

Neural Video Frame	PSNR(dB)
Frame 1	22.98
Frame 33	23.26
Frame 50	22.45
Frame 124	24.23

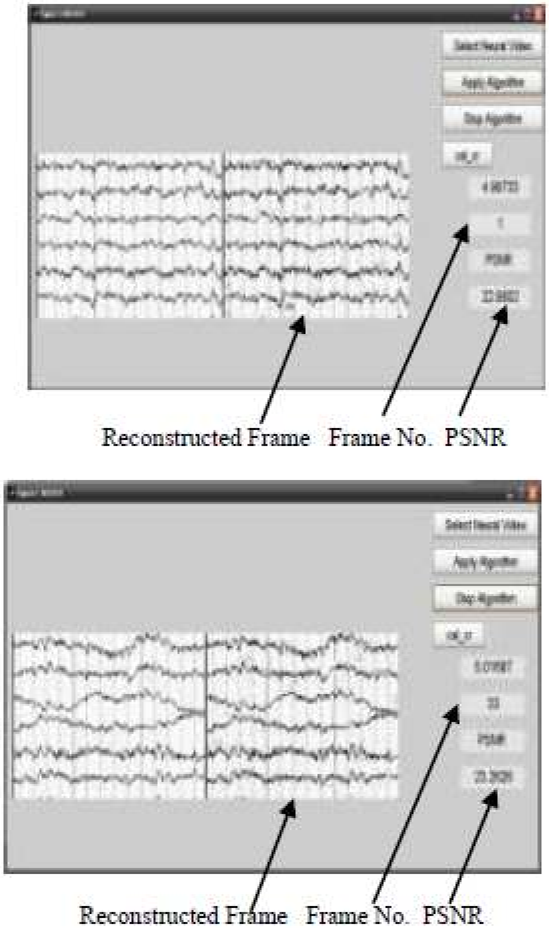


Fig 5: Reconstructed 1, 33th frames from neural Video sequence.

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