Optimal Transform of Multichannel Evoked Neural Signals Using a Video Compression Algorithm

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***Abstract*—One of the most important problems in the field of biomedical engineering is how to record a multichannel neural signal. This problem arises because recording produces a large amount of data that must be reduced to transfer it through wireless transmission, and data reduction must be made without compromising data quality. Video compression technology is very important in the field of signal processing, and there are many similarities between multichannel neural signals and video signals. Therefore, we use motion vectors (MVs) to reduce the redundancy between successive video frames and successive channels. We also test what transform for neural signal compression is best. Our novel signal compression method gives a signal-to-noise ratio (SNR) of 25 db and compresses data to 5% of the original signal.**

Keywords-biomedical signal processing; video signal processing; multielectrode signals

I. INTRODUCTION

Recently, in the field of biomedical engineering, multielectrode neural data recording has gained immense importance, especially for neuroprosthetic devices and brain-machine interfaces (BMI). Furthermore, multichannel neural recording is necessary for related bio-analyses. However, recording a large amount of data remains a challenging task. The amount of recorded data tends to exceed the data capacity of state-of-the-art wireless links that are used for biological applications. Wireless transmission can be used to conduct experiments on animals that are not anesthetized and exhibit spontaneous behaviors.

Spontaneous signals produce good results, such as so-called NPU (Neuro Processor Unit) [1][2][3][4]. Clear signals, which are easily detected by simply setting a threshold, are often emitted spontaneously from a single neuron (Fig. 1A). Consequently, 0–1 signals can be transmitted with or without spiked pulses and data can be compressed. On the other hand, evoked signals are often emitted from a bundle of neurons and not from a single neuron. Therefore, evoked signals overlap substantially, and simple algorithms cannot be used to analyze them (Fig 1B). Researchers require complete waveforms of evoked signals for their analysis. Because an efficient data-compression algorithm is currently unavailable, existing neural signal recording systems can transfer only the *complete* waveform of a channel or the active region of a waveform. To solve this problem, we developed a new compression algorithm for evoked signals using advanced signal processing techniques.

Although multichannel evoked signals appear to contain a huge amount of data, most of the data is redundant. The correlation between successive channels is very high; according to our experimental data, an average value of more than 0.85 is obtained. This finding implies that redundancy in data can be eliminated using signal processing. In a previous study [5], an audio compression algorithm (MPEG 4 ALS) compressed neural signal data to around 1/3 of its original size. Video compression uses another powerful algorithm. We use a video algorithm to compress neural signals and the results obtained are excellent.

All biomedical chips (neural recording systems) that are implanted in a living body must operate at a very low power (less than or equal to 8–10 mW) [6]. Otherwise, chip temperature could increase, exceed 1 °C, and cause neural tissue damage. Thus, our compression algorithm must be simple and appropriate for biomedical applications such as BMI.

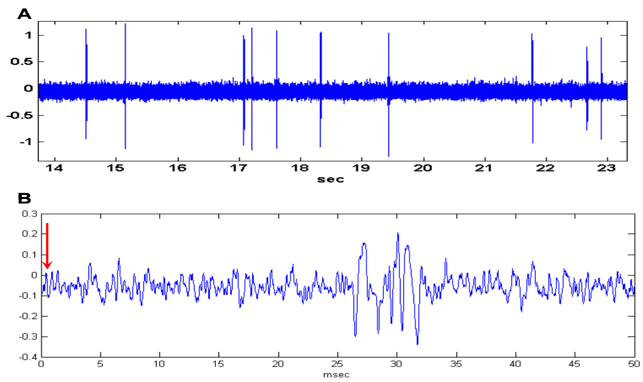

Figure 1. Recoded spontaneous (A) and evoked action potentials (B). Note the difference in the waveforms and response periods between the two kinds of signals. (The red arrow indicates the incidence of responses to mechanical stimulation)

This paper presents a novel algorithm that compresses data for multichannel neural signals to only 5% of the original data amount and maintains the complete waveform of the signal at low power. The algorithm is based on our successful single-channel result [7].

II. Data And Experiments

Qualified mechanical stimuli were applied to the tail of a Wistar rat. Subsequent neuronal responses were recorded using a glass microelectrode positioned on the rat's primary somatosensory cortex (S1). The low-frequency components of neuronal signals were filtered with a fifth-order Bessel filter having a passband of 330 Hz to 10 kHz. Data were then acquired at 100 kHz using a 12-bit AD card (PCI-MIO-16E-4, National Instrument) and a LabVIEW user interface (Fig. 2).

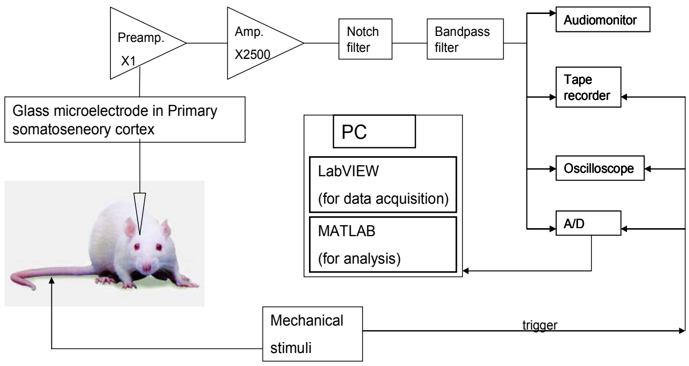

Figure 2. Experimental setup of the recording system

The mechanically evoked action potentials recorded in the experiment were mediated by Aβ fibers from the peripheral nervous system (PNS) to the central nervous system (CNS). Potentials were recorded 25 to 40 ms after the onset of the stimulation. The spikes evoked by the mechanical stimuli overlapped significantly, and hence, a considerable number of neuronal ensembles were produced in response to the stimuli in S1 of the rat. Therefore, the main characteristics of our signal were overlapping spikes that occurred within a small period of time, approximately 15 ms.

III. Neural Video Sequence Set

Before proceeding with the signal processing, we present a simple transform on the neural signal because the neural signal range is different from that of a video signal. However, the precisions of the neural and video signals are similar—8 bits [6][8]. Owing to this characteristic, we transform the neural signal to 0–255 (128 on average) using a linear transform so that the signal fits the video compression algorithm.

To apply video compression to multichannel neural signals, it is necessary to generate a "pseudo-neural" video sequence. This sequence has a strong influence on results. To analyze the method of generation of the sequence and to remove spatial redundancy, it is necessary to know the operation of the video compression algorithm.

A. Motion vector (MV)

In the video compression algorithm, MVs play an important role in providing a remarkable compression rate. For example, a common video compression algorithm can compress a broadcast video sequence, achieving a frame rate of 30 fps, frame size of 720 × 480, 8 bits/pixel, and a data transfer rate ranging from 248.83 Mbps to 3–8 Mbps. Thus, a large amount of data can be saved (around 96.8% to 98.8%).

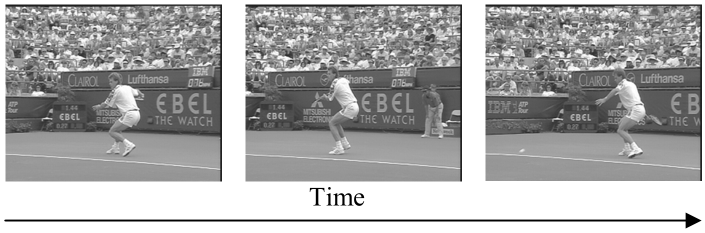

Figure 3. Images in video sequence (Stefan.y)

The MV helps to reduce spatial redundancy. Fig. 3 shows a common sports sequence (Stefan.y). From the figure, it can be observed that the background of the photograph does not change significantly, although the athlete moves from left to right. Thus, the MV can be located between successive frames; we record only the difference between frames by searching the similar parts with MVs. Spatial redundancy is eliminated and the amount of data needed for recording is reduced considerably.

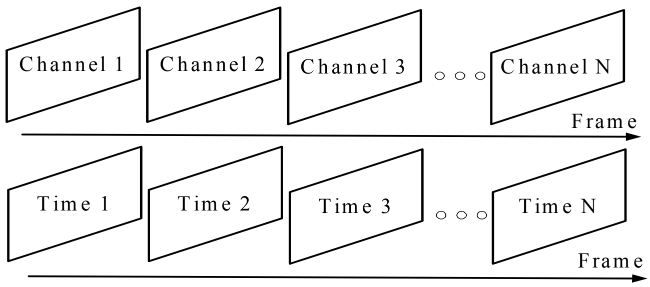

Figure 4. Two methods for generating a multichannel neural video sequence. Top: set signals from channel N (electrode N) as frame N and bottom: set signals at time N as frame N.

B. Frame setting

Fig. 4 shows two methods for generating a multichannel neural video sequence. In one method, signals from channel 1 are set as frame 1, signals from channel 2 are set as frame 2, and so on. In the other method, signals at time 1 are set as frame 1, signals at time 2 are set as frame 2, and so on. The choice of which method to use depends on whether the neural signals have a high correlation between successive channel frames or between successive time frames. If the correlation is high, then the MV technique can be used to reduce redundancy and obtain better performance efficiency in the compression algorithm.

C. Biomedical and electrophysiological analysis

A correlation between successive channels is observed in electrophysiological analysis. When a multielectrode probe detects nearby firing neurons, more than one channel will record the neuronal signals. If a channel is close to the firing neuron, then the signals will be advanced. If not, then the signals will be delayed. These signals will transmit and decay [9]. If the distance between neighboring channels is very small, then their time difference will be very small and the correlation between channels will be high. (Table 1)

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

The correlation between electrodes 8&9 and 9&10 is low because electrode 9 is broken. It becomes difficult to carry out experiments when only 16 of the available channels are working properly. Despite this difficulty, a high correlation working electrodes is obtained.

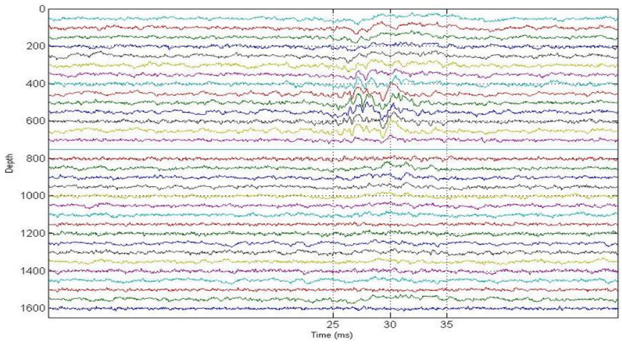

Figure 5. Experimental data for the multichannel neural signals. A stimulation is applied at time 0, and the analysis is carried out 25–35 ms later.

Although setting time 1 as frame 1 appears to be rational for signal processing, bio-knowledge has a different explanation for the same. Researchers analyze the the same experiments at different times for different interpretations Even if they are same experiments, researchers still treat them as an independent experiment.

We decided to generate a neural video sequence using correlations between neighboring channels. Owing to the nature of evoked signals, it is only possible to record and compress the signals at 25–40 ms after the stimulation. The sampling rate is 64 kHz. Therefore, for 1024 samples that are between 25–40 ms and consist of 16 ms of data, the size of each frame is 32 × 32 pixels. Each electrode has 16 channels, and therefore, each trial has 16 frames. Since each experiment has 20 trials, there are 320 frames in all. These 320 frames form our "pseudo-neural" signal sequence.

IV. VIDEO COMPRESSION ALGORITHM

The presently used video compression algorithms such as H.264, scalable video compression (SVC), and multiview compression are very complex. Hence, we used a neural signal compression algorithm because of its low power. However, a complex algorithm delivers a better performance than a simple one at a high-computational cost. Fig. 6 shows a block diagram of the algorithm.

Since a trial comprises 16 frames, every set of 16 frames is placed into a single group. The first frame of the group uses intra-frame coding, while the rest of the frames use the said inter-frame coding. We use the previous frame to determine the MV, and then, we perform video compression flow, motion estimation, and motion compensation. After transformation on the residue, quantization is performed.. Entropy coding makes the output stream more efficient. However, we do not use any complex entropy coding, such as that reported in [10]. We simply use run-length coding, Huffman coding, and arithmetic coding.

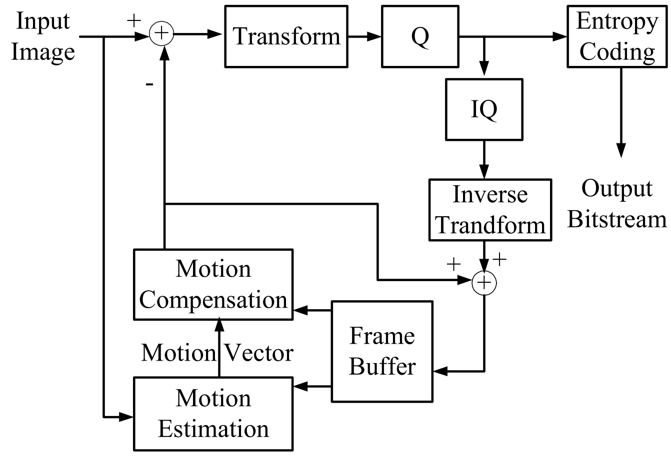

Figure 6. Block diagram of video neural signal compression.

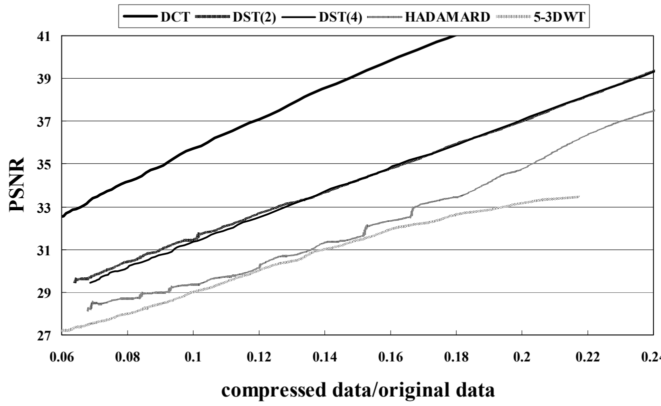

Figure 7. Comparison of different transforms. Discrete Cosine Transform (DCT) outperforms all other transforms.

V. COMPARSION OF VARIOUS TRANSFORMS

The MV technique can help us to reduce temporal redundancy, but a transformation to reduce spatial redundancy is still needed. In video/image compression, the Discrete Cosine Transform (DCT) is used to reduce redundancy. However, our objective is to compress a neural signal. Thus, we conducted compression experiments using a group of different transformations to determine the best transformation for neural signal compression.

(1) $c_k = s_k \sqrt{\frac{2}{N}} \sum_{i=0}^{N-1} f_i \cos \frac{\pi}{N} k(i+\frac{1}{2})$ Discrete Cosine Transformation

(2) $c_k = s_{k+1} \sqrt{\frac{2}{N}} \sum_{i=0}^{N-1} f_i \sin \frac{\pi}{N} (k+1)(i+\frac{1}{2})$ Discrete Sine Trans. base Ⅱ

(3) $c_k = \sqrt{\frac{2}{N}} \sum_{i=0}^{N-1} f_i \sin \frac{\pi}{N} (k+\frac{1}{2})(i+\frac{1}{2})$ Discrete Sine Trans. base Ⅳ

where $s_k=1/\sqrt{2}$ for k=0 and N, and $s_k=1$ otherwise.

(4) 5-3 Discrete Wavelet Transform.

Low pass filter coefficients: $h_0=6/8$, $h_1=2/8$, $h_2=-1/8$.

High pass filter coefficients: $h_0=1$, $h_1=-1/2$

(5) Define the identity $H_0=1$ and then $H_m = \frac{1}{\sqrt{2}} \begin{pmatrix} H_{m-1} & H_{m-1} \\ H_{m-1} & -H_{m-1} \end{pmatrix}$

Hadamard Transform

As shown in Fig.7, the DCT outperforms four other transformations. For the same-bit-number criterion, the DCT has the best Peak Signal-to-Noise Ratio (PSNR). Further, the DCT has the best energy-packing characteristics; consequently, after quantization and entropy coding, it has a good compression rate. Based on these results, we chose to use the DCT in our neural signal compression algorithm

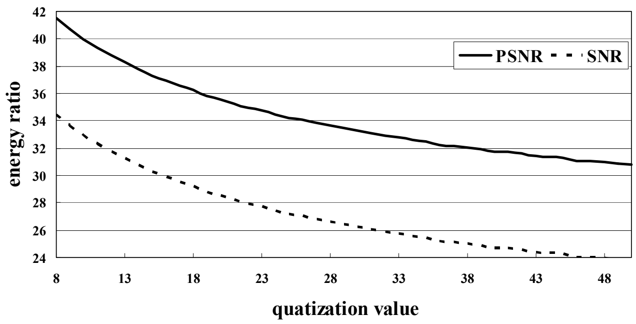

Figure 8. Energy ratio vs quantization value obtained after DCT

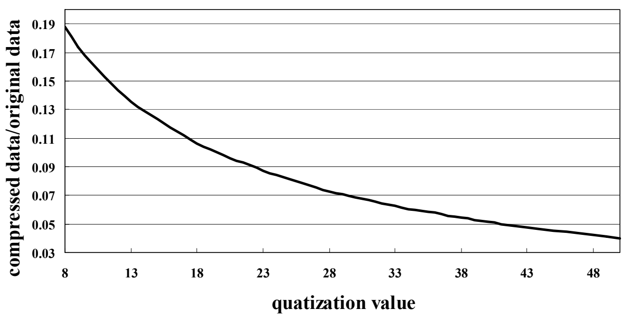

Figure 9. Ratio of compressed data amount and original data amount vs quantization value obtained after DCT

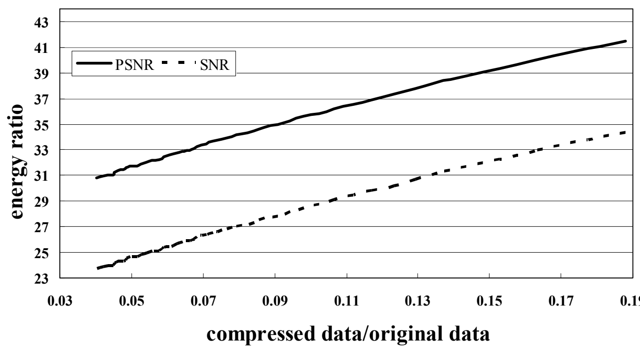

Figure 10. R-D curve: energy ratio (SNR and PSNR) vs compressed data amount and original data amount

VI. Results

In this study, we used different quantization values for different applications. From Fig. 8 & 9, we can see that a high quantization value decreases the amount of compressed data and the quality. However, as shown in Fig. 10, a trade-off between the amount (bits) and quality of data (SNR & PSNR) is likely to occur. From these two figures, we can choose a quantization value that is appropriate for a specific application. Our experiments indicate that an SNR of 25 db is adequate for researchers to carry out further analysis. In our experiments, the amount of data after compression is less than 5% of original amount. This remarkable result shows that 16-channel signals can be reduced to a 1-channel signal or less.

VII. Conclusion

Neural signal processing will undoubtedly have more extensive applications in the future. Multichannel signals are particularly important because many analyses require them, such as the analysis of overlapping spikes. At present, owing to advanced digital-signal processing and improved semiconductor technology, low power and rapid low-cost computation can be realized together. In this study, we applied a video compression algorithm for multichannel neural signal processing and obtained excellent results. In the future, we will conduct a study on the importance of digital signal processing (DSP) in bio-research.

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