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Multichannel Evoked Neural Signal Compression Using Advanced Video Compression Algorithm

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Abstract—**Multichannel neural recording is one of the most important topics in the field of biomedical engineering. 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. In this study, we propose a signal compression method that employs motion vectors (MVs) to reduce the redundancy between successive video frames and between successive channels. The method shows a signal-to-noise (error) ratio (SNR) of 25 db and data are compressed to 5% of their original size.**

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

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). Furthermore, multichannel neural recording is commonly used and is necessary for bioanalysis. However, recording large amounts of data has been a challenging task; for example, a typical recording experiment in which data is obtained from a 100-channel electrode array at the rate of 64 kHz per channel with 12-bit precision yields a data rate of around 76.8 Mbps, which is much beyond the capacity of state-of-art wireless links that are used in biological applications. Wireless transmission can be used for conducting experiments on freely behaving primates and animals.

Spontaneous signals have some good solutions, such as the so-called Neuro Processor Unit (NPU) [1][2][3][4]. The reason is that spontaneous signals are often emitted from a single neuron, which can be easily detected by simply setting a threshold (Fig. 1A). Therefore, 0-1 signals (with or without spikes) can be transmitted and the spontaneous neural signals can be compressed. On the other hand, evoked signals are often emitted from a bundle of neurons and not from a single neuron. Therefore, there is significant overlap of evoked signals, and hence, it is not possible to employ simple algorithms for analyzing them (Fig. 1B). Researchers require complete waveforms of the evoked signals for the analysis of

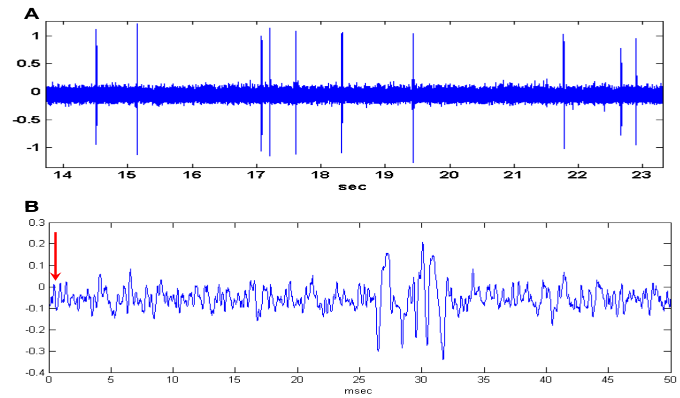

Figure 1. Recorded spontaneous (A) and evoked action potentials (B). Note the difference in the waveforms and response periods between the two kinds of action potentials. (The red arrow indicates the incidence of responses to a mechanical stimulation.)

the signals. Because of the lack of an efficient data compression algorithm, existing neural recording systems can transfer only the *complete* waveform of a channel or the active region of a waveform, even in the case of the 0-1 digital signal. In order to solve this problem, we intend developing an appropriate compression algorithm for evoked signals using advanced signal processing techniques.

Though multichannel evoked signals appear to contain a huge amount of data, most of the data is redundant. The correlation between the data in successive channels is very high; in our experiment, an average value of more than 0.85 is obtained. This implies that redundancy in data can be eliminated using signal processing. In a previous study [5], an audio compression algorithm (MPEG 4 ALS) was employed to compress neural data to around 1/3 of their original data amount. A video compression algorithm can also be effectively used to compress large amounts of data. In this study, we use a video compression algorithm to compress neural signals.

Another important requirement in a neural recording system is that it must be capable of operating with a low power. All biomedical chips that are implanted in living bodies must be capable of operating at a very low power (less

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than or equal to 8–10 mW) [6], failing which the temperature increase would exceed 1°C and cause neural tissue damage. Thus, a compression algorithm intended for biomedical applications must be simple, such as in BMI.

This paper presents a novel algorithm for compressing multichannel neural data to only 5% of the original data size while retaining information on the complete waveform of the signal represented by the data using a low power technique. The algorithm is based on the algorithm used for the successful compression of single-channel data in a previous work [7].

II. DATA AND EXPERIMENTS

Neuronal responses to appropriate mechanical stimuli applied to the tail of a Wistar rat were recorded using a glass microelectrode positioned in the primary somatosensory cortex (S1) of the rat. The low-frequency components of the signals were filtered using a fifth-order Bessel filter with 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) with a LabVIEW user interface (Fig. 2).

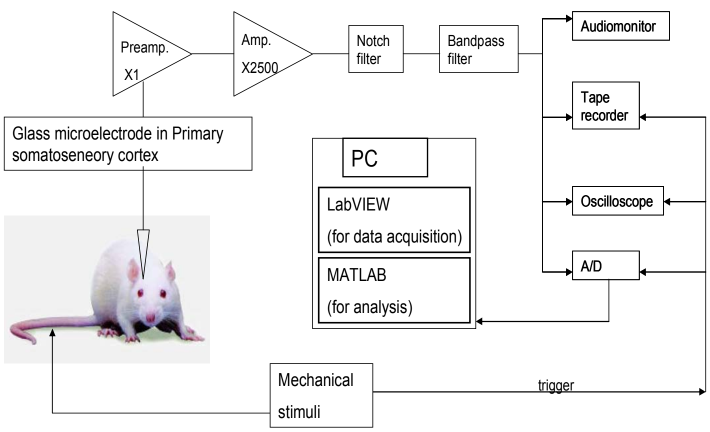

Figure 2. Setup of the recording system

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) and were determined 25 to 40 ms after the onset of the stimulation. The spikes evoked by the mechanical stimuli overlapped to a significant extent, and hence, a considerable number of neuronal ensembles responded to the stimuli in the S1 of the rat. Therefore, the overlapping spikes recorded within a small period of time, approximately 15 ms, were the main features of our signal.

III. WHY CHOOSE VIDEO COMPRESSION ALGORITHM

Before proceeding with signal processing, we shall modify the neural signal by employing a simple 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 [8] [9]. We transform the neural signal to 0–255 with an average of 128 by using a linear transform so that the video compression algorithm can be applied to it.

A. *Biomedical and electrophysiological analysis*

A correlation between successive channels is observed in the results of electrophysiological analysis. When a multielectrode probe detects firing neurons, the signals are recorded by more than one channel. If a channel is close to the firing neuron, then it receives the signals promptly. Otherwise, the signals are received after a delay. These signals will transmit and decay in the cell [10]. If the distance between neighboring channels is very small, the difference between the times taken for receiving the signals will be very small. These characteristics offers a high correlation between the channels.

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

Correlation between neighboring electrodes. The correlation between electrodes 8&9 and 9&10 appears to be low since electrode 9 is broken. It becomes difficult to carry out experiments when only 16 of the available channels are proper. Despite this difficulty, a very high correlation between the abovementioned electrodes is obtained.

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. Video signals have the same characteristic. A series of images comprise the video, but neighbor images do not change significantly (Fig. 3). Recently video compression algorithm has many skills to deal with it. That is way we choose video compression algorithm to compress multichannel neural signal.

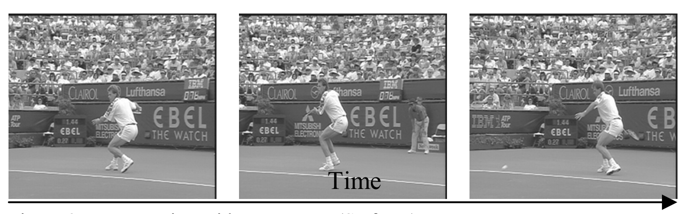

Figure 3. Images in a video sequence (Stefan.y)

B. *Motion vector (MV)*

In order to apply video compression to multichannel neural signals, it is necessary to generate a "pseudo neural video sequence." How to generate of a neural video sequence is very important because it has a strong influence. For analyzing the method of generation of the sequence, it is necessary to know the operation of the video compression algorithm in order to remove the spatial redundancy.

In video compression algorithms, MVs play an important role in providing a high compression rate. For example, a commonly used video compression algorithm (MPEG 2) can compress a broadcast video sequence to a frame rate of 30 fps, a frame size of 720 × 480, 8 bits/pixel, and a data transfer rate ranging from 248.83 Mbps to 3 Mbps. Thus, the data size can be decreased to a considerable extent (by around 96.8% to 98.8%).

The MV helps to reduce spatial redundancy. Fig. 3 shows a sport sequence (Stefan.y). From the figure, it can be observed that the background of the photograph does not change significantly, though the athlete moves from the left to the right. Thus, we can determine the MV between successive frames. 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.

C. *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, etc. In the other method, signals at time 1 are defined to lie in frame 1, signals at time 2 to lie in frame 2, etc. However, the choice of a suitable method from the two above-mentioned ones depends on whether the neural signals show a high correlation between successive channel frames or between successive time frames. This is because if the correlation is high, the MV technique can be used in the compression algorithm to reduce redundancy and obtain high performance efficiency.

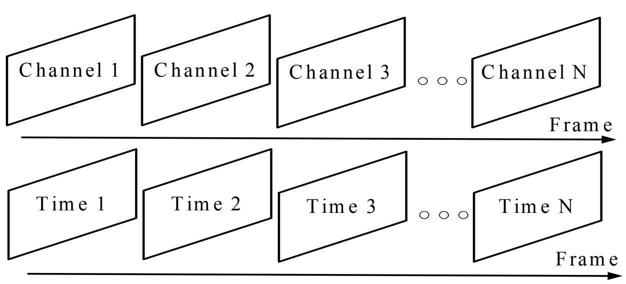

Figure 4. Two methods for generating a multichannel neural video sequence. (Above) Classify signals from channel N (electrode N) in frame N and (Below) classify signals at time N in frame N.

Although setting time 1 as frame 1 appears to be rational during signal processing, bio-knowledge has a different explanation for the same. Researchers analyze experimental results and offer different interpretations for experiments performed at different times. Even if the experiments are identical, researchers still treat them as independent experiments.

In this study, we choose to generate a neural video sequence by using the correlation between neighboring channels. Owing to the nature of the evoked signals, it is possible to record and compress the signals only 25–40 ms after the stimulation. The sampling rate is 64 kHz. Therefore, for a total of 1024 data samples, which are recorded between 25–40 ms (data for 16 ms)(Fig. 5), the size of each frame is 32 × 32 pixels. Each electrode has 16 channels, and therefore, each trial also has 16 frames. Each experiment has 20 trials for a total of 320 frames. These 320 frames form our "pseudo neural signal sequence."

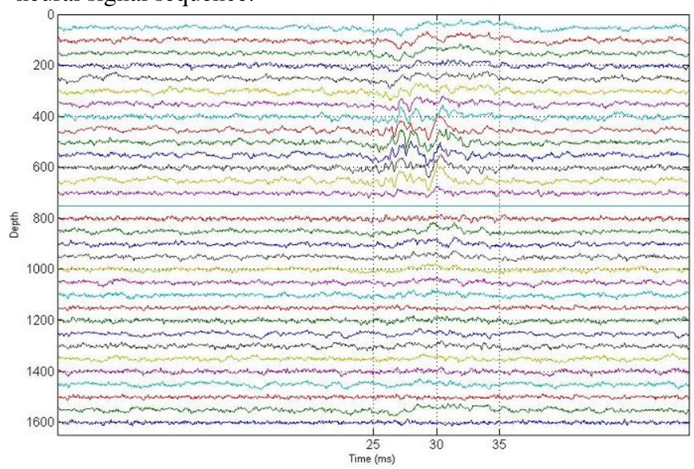

Figure 5. Multichannel neural signals used in the experiment. The stimulation is applied at time 0, and the analysis is carried out 25–35 ms after the stimulation.

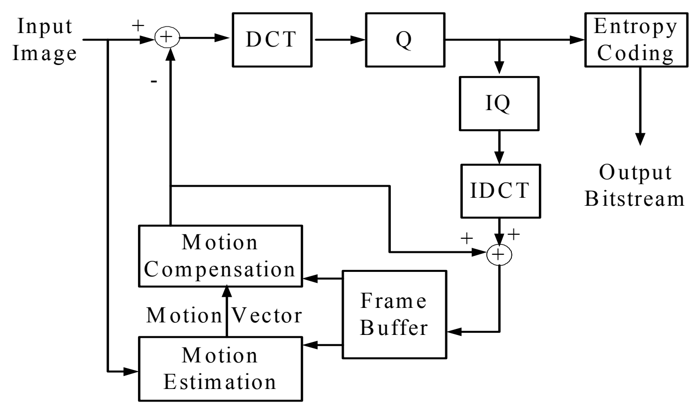

Figure 6. Block diagram for video neural signal compression.

IV. VIDEO COMPRESSION ALGORITHM

The commonly used video compression algorithms such as H.264, scalable video compression (SVC), and multiview compression are very complex. Hence, we use a very basic (simple) video compression algorithm because of its low power. However, a complex algorithm shows better performance than a simple algorithm, albeit at a high-computational cost. In Fig. 6, we present the flow chart of the proposed algorithm.

Since a trial comprises 16 frames, we consider the frames of a trial as a single group. The first frame of the group uses intra-frame coding, while the rest of the frames use the inter-frame coding. We use the previous frame to determine the MV of a frame, and then perform video compression flow(Fig. 6), motion estimation, and motion compensation. After discrete cosine transformation (DCT) of the residue, quantization is performed. Entropy coding increases the efficiency of the output stream. However, we did not use any complex entropy coding such as that reported in [11]. We only used run-length coding, Huffman coding, and arithmetic coding.

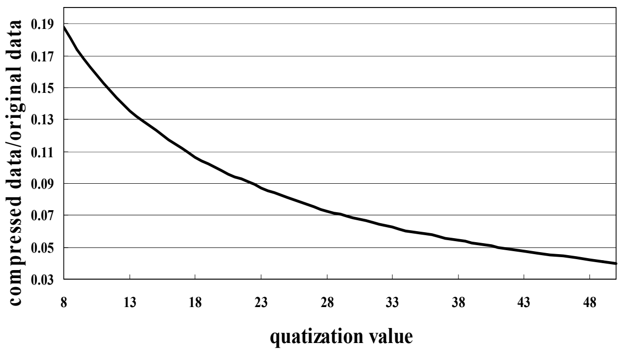

Figure 7. Ratio of compressed data size to original data size vs. quantization value obtained after DCT.

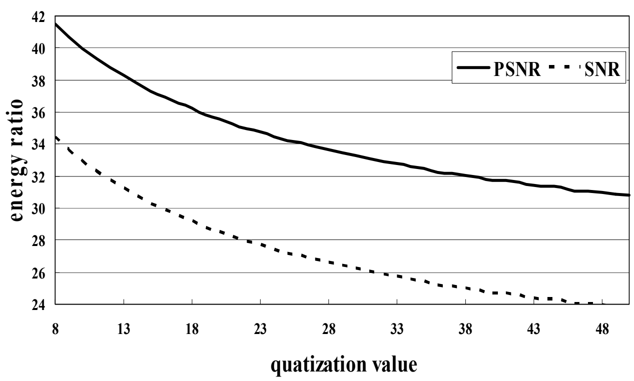

Figure 8. Energy ratio (SNR and PSNR) vs. quantization value obtained after DCT.

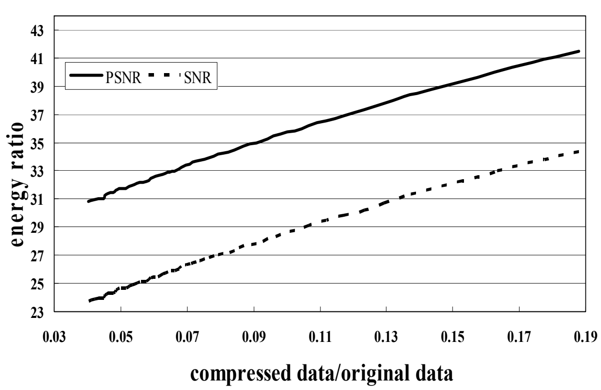

Figure 9. R-D curve: energy ratio (SNR and PSNR) VS the ratio of the compressed data size to the original data size.

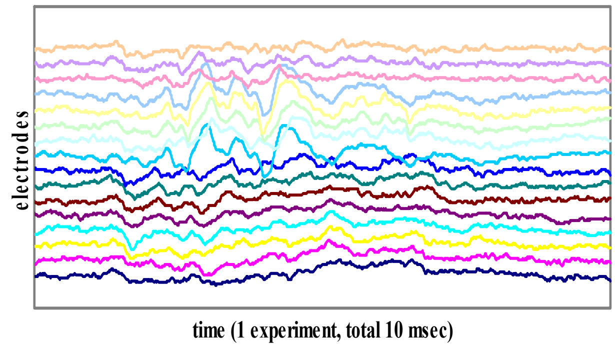

Figure 10. Original signal, total 16 electrodes signals, sorting by the depth .

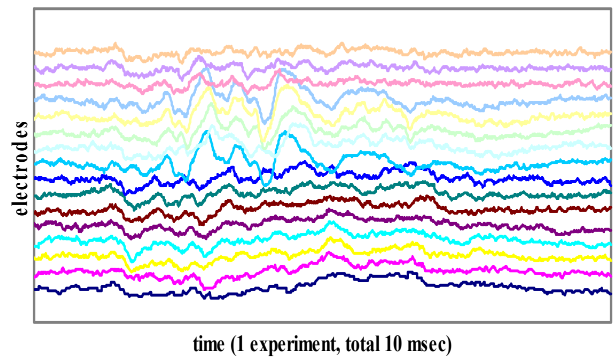

Figure 11. Compressed signals (SNR=35db, 20% data amount of original signals), total 16 electrodes signals, sorting by the depth

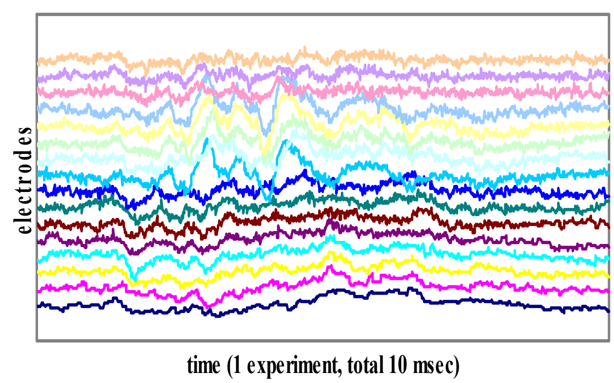

Figure 12. Compressed signals (SNR=25db, 5% data amount of original signals), total 16 electrodes signals, sorting by the depth

V. RESULTS

In this study, we provide different quantization values for different applications. From Figs. 7 and 8, we can observe that a high quantization value decreases the extent of data compression and leads to a low signal-to-noise-ratio (SNR) or a low peak-signal-to-noise-ratio (PSNR). However, it is likely that there is a trade-off between the extent of compression (bits) and the quality of data (SNR and PSNR). Fig. 9 clearly shows the existence of such a trade-off. From these figures, we can choose an appropriate quantization value. From our experiments, it is seen that an SNR of 25 db is adequate for researchers to carry out further analysis. (We provided the bio-team with several different SNR data sets, and they inferred that a value of 25 db is adequate.)(Fig. 10,11,12) The size of the compressed data in our experiments is less than 5% of the original data size. The obtained result is therefore significant and shows that 16-channel data can be compressed to single-channel data or to a greater extent (16 * 0.05 =0.8< 1).

VI. CONCLUSION

Neural signal processing will undoubtedly have wide applications in future. Multichannel signals are particularly important because many analyses such as the analysis of overlapping spikes cannot be carried out without using these signals. At present, owing to the development of advanced digital signal processing techniques and improved semiconductor technology, low power and rapid computation can be realized together. In this study, we use a video compression algorithm for multichannel neural signal processing and obtain excellent results. In the future, we want to design a dedicate hardware for this algorithm. We intend presenting a study on the importance of digital signal processing (DSP) in bioresearch, such as computational and memory requirements of the algorithm.

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