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Real-Time Somatosensory Evoked Potential Monitoring using FPGA-based Adaptive Filter

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***Abstract*—This study was to analyze the performance of fixed-point adaptive signal enhancer (ASE) for somsatosensory evoked potential (SEP) measurement. An animal study was conducted to evaluate the usefulness of this technique in detection of spinal cord injury. The ASE technique has been reported powerful to improve signal to noise ratio of SEP. Therefore,we proposed an integrated circuit. module to perform real time ASE for fast SEP measurement, and a fast fixed-point algorithm was employed in the Field Programmable Gate Array design. We compared the SEP results from FPGA-beased ASE methods and the conventional ensemble averaging (EA) method during an animal experiment. Experimental results on a spinal cord compressive injury model showed that the FPGA-based ASE methods have superior performance over the EA method. It would be helpful to design fixed-point ASE based on FPGA for real-time monitoring of intraoperative SEP.**

I. INTRODUCTION

Intraoperative somatosensory evoked potential (SEP) monitoring is becoming a common adjunct to detect changes in spinal cord function. In the case of spinal surgery, where instrumental compression or excessive traction may happen during the correction of spinal distortion, SEP monitoring has become essentially indispensable because it is able to provide the surgeons with immediate identification of any possible spinal cord injury to ensure that appropriate action at the first time before any irreversible neurological impairment becomes permanent [1]. However, SEP signals are usually contaminated by large amount of noises, including instrumental interference, surrounding power lines, and electrophysiological signals like electroencephalography (EEG) from the subjects [2]. Various signal processing methods have been applied during the SEP recording to improve the signal-to-noise ratio (SNR) of SEP. In clinical practice, monitoring of SEP is mainly based on the ensemble averaging (EA) to measure evoked potentials. The EA method usually takes the average of 100-500 trials of the raw SEP signal recorded continuously as an indication of the spinal cord function. However, the EA method by nature suffers a defect of time-consuming and low-efficiency. In general, the EA method requires several minutes to measure the average and takes up as long as half an hour to provide the feedback to the surgeons. As a result, it inevitably decreases the effectiveness of monitoring and unnecessarily increases the risk of surgery. Recently, adaptive filtering emerged as a highly reliable and efficient technique for extraction of evoked potential [3] and [4]. Different types of adaptive filtering algorithms were proposed for various types of evoked potentials, and a least mean squares (LMS)-based adaptive signal enhancer (ASE) has been proved to be a fast, simple, and reliable SEP extraction method for intraoperative spinal cord monitoring, [5]-[7].

Unfortunately, most past reports of ASE were carried out in personal computer and limited by computation speed, and few papers have focused on real-time monitoring, which can be conveniently solved by a dedicated hardware implementation using a Field Programmable Gate Array (FPGA) [8].

In practice, FPGA design can be presented by either fixed-point or floating-point algorithm. In contrast, fixed-point algorithm costs less FPGA resources, less energy-consumption and has faster speed and lower complexity for hardware design [9]. So, fixed-point algorithm would take the place of floating-point if it has equivalent or better performance than floating-point algorithm. Consequently, it is valuable to investigate the performances of the two algorithms for the real-time signal processing based on FPGA. Accordingly, this study has analyzed the outputs of fixed-point algorithm ASE, and compared with the traditional EA SEP detection.

II. MATERIALS & METHOD

A. Animal Experiments

A reported rat model [10] was adopted to evaluated the FPGA based ASE and EA SEP in different spinal cord compression levels.

Eighteen mature rats, weighing between 260 and 280g were included in this study. All the surgical procedures were performed under intravenous pentobarbitone (0.05mg/g) aneasthesia augmented by local 1% xylocaine infiltration. Additional pentobarbital was given at intervals and in amounts established in non-curarized rats to assure adequate anesthesia.

The stimulation and recording methods used for SEP tests were similar to those used in routine clinical spinal cord

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monitoring. The spine was exposed posteriorly from the 4th cervical vertebra to the 4th lumbar vertebra, as shown in Figure 1. SEP was evoked by hind paw stimulation and recorded from the skull.

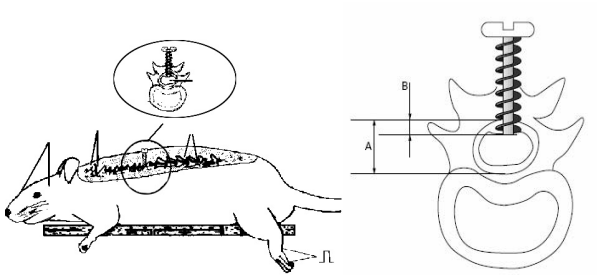

Figure 1. Animal model for spinal cord injury [10].

The mechanical injury to spinal cord was simulated by an inserted screw. Before the injury to spinal cord occurred, EP normal waveforms in different modalities were recorded as baseline.

After the spine was exposed, a narrow cylindrical hole was drilled longitudinally through the posterior spinal process of one of the vertebrae between T4 and T7 from its caudal point down to the root of the spinous process. A 0.6mm thread screw was then positioned in the hole (Figure 1), and the screw carefully and slowly advanced into the spinal canal. At the same time, SEP signals were recorded and the number of turns of the screw noted, until the screw touched the inner-wall of vertebral body.

The animals were then sacrificed with an overdose of pentobarbitone. The vertebral segment with screw was sectioned. The screw was slowly loosened and the compression ratio was measured by visual assessment. As shown in Figure 1, the compression ratio is defined as:

$$\text{Compression ratio} = \frac{B}{A} \times 100\% .$$

Where B isdepth of the screw, A is original anterior-posterior diameter of the spinal canal.

The turn numbers noted were used as an index to define the compression ratio at each SEP recording. The data recorded at compression ratios closest to 30%, 50% and 100% were then selected for analysis.

B. Ensemble Averaging (EA):

The conventional EA method for SEP extraction was first introduced. Suppose we have M trials of SEP signals $x_i(n)$, $i = 1,2,\cdots,M$, in one recording session, the EA result is obtained as

$$y_{EA}(n) = \frac{1}{M}\sum_{i=1}^{M} x_i(n) , \quad (1)$$

where n is the time index, $n = 1,2,\cdots,N$, and N is the total number of samples of one SEP trial.

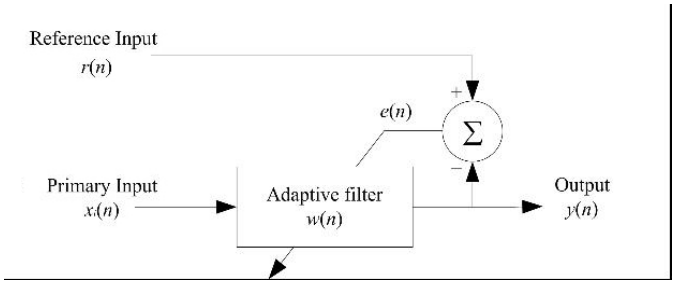

Figure 2. A two-channel ASE for SEP extraction.

C. Adaptive Signal Enhancer (ASE):

The block diagram of a ASE for SEP extraction is illustarted in Figure 2. The input signal is the raw SEP trial $x_i(n)$, and the reference signal $r(n)$ is generally obtained as the EA of large numbers of SEP trials. The output signal $y(n)$ is estimated as

$$y(n) = \sum_{p=0}^{P-1} w_p(n) x_i(n-p) , \quad (2)$$

where $w_p(n)$ is the coefficients of the adaptive filter and P is the order of filter. Eq. (2) can be futher written in matrix form:

$$y(n) = X^T(n) W(n) , \quad (3)$$

where $X(n) = [x_i(n), x_i(n-1), \cdots, x_i(n-P+1)]^T$ and $W(n) = [w_0(n), w_1(n), \cdots, w_{P-1}(n)]^T$.

The filter coefficients $W(n)$ and the output $y(n)$ can be recursively estimated using the LMS algorithm[11]. as

$$e(n) = r(n) - X^T(n) W(n) , \quad (4)$$

$$W(n+1) = W(n) + 2\mu e(n) X(n) , \quad (5)$$

where μ is the step-size parameter.

D. Fixed-point FPGA

The key to exchange from floating-point to fixed-point algorithm is word-length, round-off and overflows [12-14]. In hardware generation, the bit length of variables in a program is closely related to the area, operation precision and speed of the hardware. Therefore, tradeoffs related to precision exist, which must be dealt with delicately. The problem is twofold: first, how to balance between the need of reasonable numeric precision, which is important to accuracy and convergence, and the cost of area of the FPGA. Second, how to choose a suitable bit length whose dynamic range is large enough to guarantee that saturation, as well as the stalling phenomenon will not occur for a particular application [15]. In this particular design, for simplicity and clarity, the bit lengths for all intermediate results are truncated to be equal to the bit lengths of the operands, by removing the lower significant bits but preserving the sign bit. In this paper, in order to minimize the cost of area of the FPGA, the shortest word-length, 16 bits, is chosen to satisfy the numeric precision.

III. RESULTS

For each rat in those four stages (baseline and, 30%, 50%, 100% compression), 500 trials of SEP in total were collected and the EA results of the 500 trials (EA500) were considered as the benchmark for comparison. The EA results of the first 200 trials in the first stage (baseline) were used as the reference signal, $r(n)$, for ASE during different stages in the flowing recordings. Then, the next 100 trials (201-300) of the first stage were processed with two SEP extraction methods, EA, FPGA-ASE, respectively. In the other three stages of spinal cord compression, the first 100 trials were processed by EA and ASE methods, respectively. This design enables an objective comparison of the performances of SEP detection methods using the same set of raw SEPs, which shares the same systemic variables fluctuation such as temperature, blood pressure, and noise condition.

Figure 3 shows an example of SEP extraction in the first stage based on 50 trials. It can be seen that FPGA-ASE SEP from 50 trials can achieve the satisfactory result, even better than 500-trials EA-SEP, while the raw SEP signal (Figure 3a) was buried in the heavy noise.

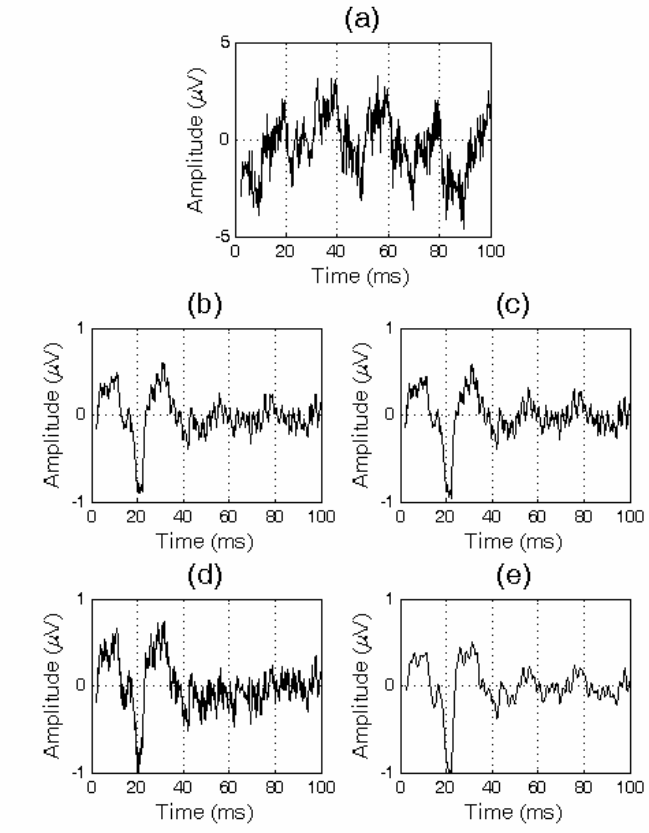

Figure 3. An example of SEP waveform and the ASE results: (a) single-trial raw SEP signal; (b) 500-trial EA-SEP; (c) reference SEP signal; (d) 50-trial EA-SEP; (e) FPGA-ASE-SEP from 50 trials.

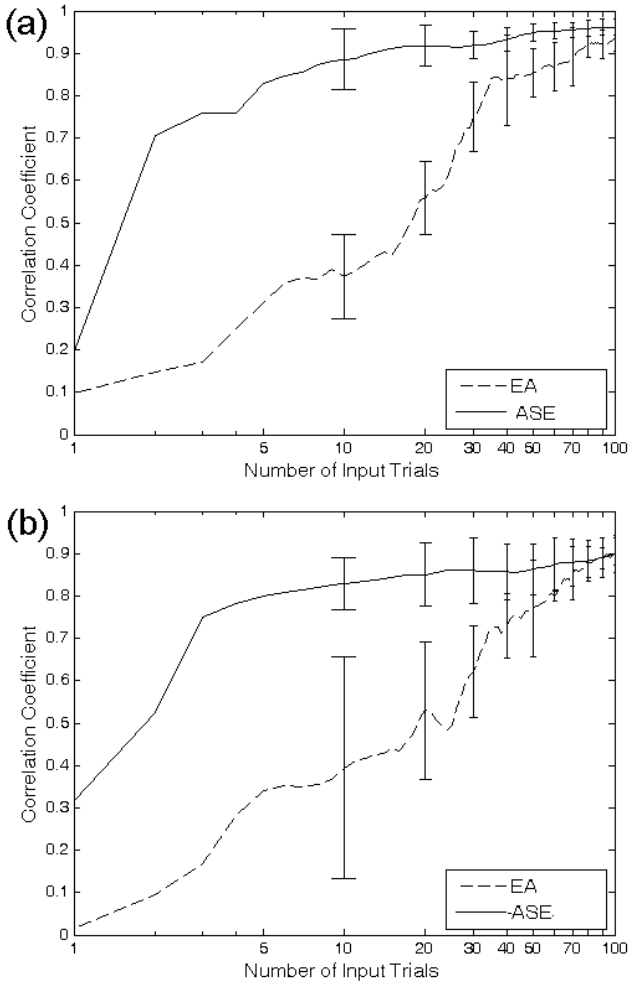

Figure 4. Comparison of correlation coefficients between EA-SEP/FPGA-ASE-SEP and EA500 in neurological normal condition (a) and 50% compression condition (b).

The correlation coefficients were calculated between the EA500 waveforms and the outputs of FPGA-ASE-SEP and EA-SEP. A comparison of EA and FPGA-ASE in few trials SEP recordings was shown in Figure 4, where the correlation coefficients (mean ± standard deviation) of two stages (baseline and 50% compression) were plotted.

Figure 5 illustrates the EA500-SEP and SEP waveforms processed by EA and FPGA-ASE after 50 trials in four different stages. It can be seen that, using the FPGA-ASE, the changes of the amplitude and latency during different stages are clearer than that of EA method,

IV. DISCUSSION & CONCLUSION

SEP monitoring is a common technique to detect changes of spinal cord function in spinal cord surgery. However, SEP signals are usually corrupted by noises from background on-going activities, resulting in a poor signal-to-noise ratio as low as -20 ~ -30dB, which makes peak identification difficult and often precludes accurate latency and amplitude measurements. In this study, an

FPGA-based ASE was introduced to perform real-time SEP monitoring during spinal cord compression.

This study made use of animal spinal cord injury model to simulate intraoperative SEP changes during spinal surgery. The results can be used to evaluate the clinical usefulness of FPGA-based ASE. The major merit of FPGA-based ASE is its ability to extract SEP for amplitude/latency measurements with comparable reliability to that of conventional EA, but with 20% of input trials. The experimental results showed that FPGA-based ASE had better performance than EA.

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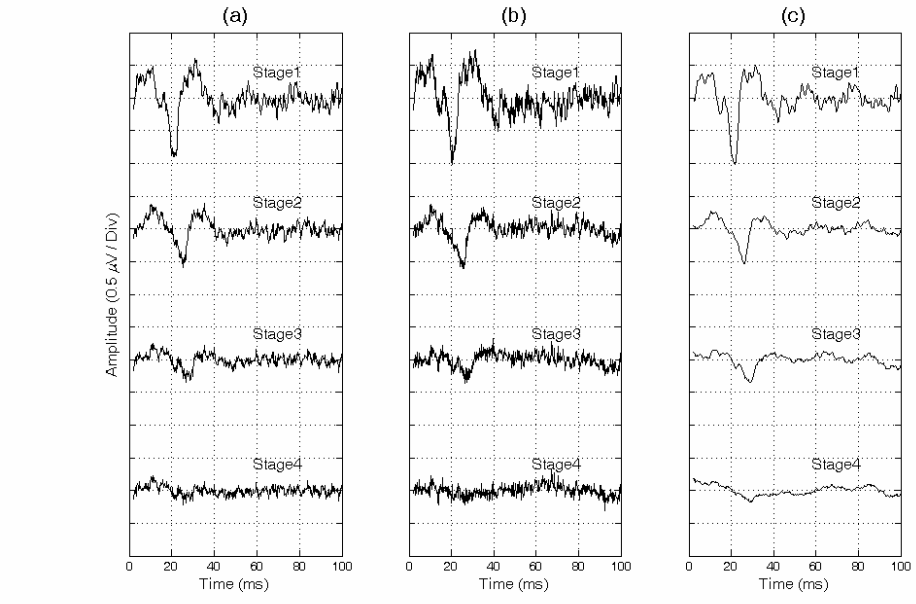

Figure 5. Illustration of SEP waveforms by EA and ASE during different experimental stages: (a) EA500 SEP; (b) 50-trial EA-SEP; (c) FPGA-ASE-SEP extracted from 50 trials.