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A 128-Channel Extreme Learning Machine-Based Neural Decoder for Brain Machine Interfaces

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ABSTRACT: *In the paper we discuss about the extreme learning machine (ELM) interface which has potential to restore the lost sensorimotor functions in people. The key element used in brainmachine interface (BMI) is neural decoder. Extreme learning machine interface controls the external devices by modulating their neural activity. A mathematical algorithm is introduced to record the neural activity in extreme learning machine interface. The proposed system utilizes a decoder to initialize the feedback approach. A motor ELM is modelled as closed loop control system, where the controller is brain. At last the proposed system takes limited number of input channels and reduces the number of programmable weights.*

KEY WORDS: Brain machine interface (BMI), Extreme learning machine (ELM), neural decoder, neural network.

I.INTRODUCTION

Brain-Machine Interfaces (BMIs) have the potential of helping patients with motor disabilities to restore some of their lost motor functions. BMIs typically use a decoding algorithm to translate the recorded neural activity into a control signal to actuate an external device. In closed-loop neural decoding, the BMI subject receives visual feedback in real time that allows the subject to correct movement errors to enhance control performance. Brain-Machine Interfaces (BMIs) have the potential to restore lost motor functions for patients with severe motor disabilities. In cortically-controlled BMIs, neural activity I recorded from ensembles of neurons using multi-electrode arrays implanted in the subject's cortex and is then translated in real-time by neural decoders into motor commands that actuate an external device Such as a robotic arm.

A key element of this process is the neural decoder, which is typically designed using a biomimetic approach that relies on the concurrent recording of the neural activity and the actual (or imagined) arm movement.

This approach assumes that movement parameters are 'encoded' in the activity of the neuronal ensemble, and that a BMI algorithm can 'decode' such movement representation in order to control an external device. It also assumes precise synchrony between neural and kinematic or motor imagery data, which may not be known, for example, in the case of self-paced movement initiation. In addition, the collection of such training data. Imposes a practical problem for the ultimate clinical application in which users are unable to produce overt movements or constantly need a caregiver to calibrate the decoder on a daily basis. From below figure (1) we can observe that BMI as closed loop control system.

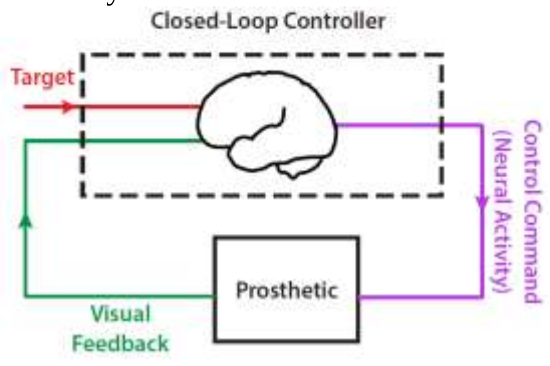

Fig. 1. BMI as closed loop control system

A closed-loop controller controls a plant using commands that are decided based on the plant's forward dynamics model and the real-time feedback of its current state. In the

Case of a motor BMI, the controller is the brain, the plant is the external device (e.g., the robotic arm) to be controlled, and the feedback is the biofeedback received by the brain. The majority of BMI decoders were

Trained in an open-loop manner. Decoders can also use as input the spike events, which indicate the presence or absence of a spike at a given time. Thus using insights and tools from control theory could guide the design of decoding algorithms to further make them tailored to the brain system.

II.LITERATURE SURVEY

In this paper, we present a machine learning coprocessor (MLCP) achieving low-power operation through massive parallelism,Sub-threshold analog processing and careful choice of algorithm. The below figure (2) contrasts our approach with traditional approaches. Our MLCP acts in conjunction with the digital signal processor (DSP) already present in implants (for spike sorting, detection and packetizing) to provide the decoded outputs.

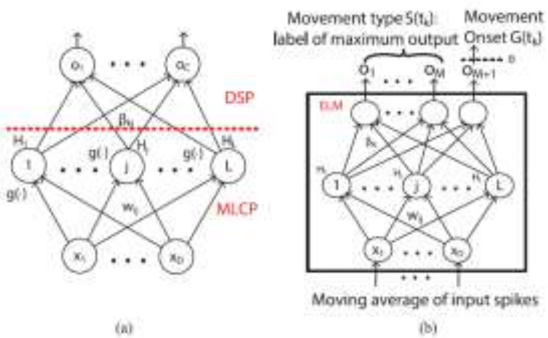

Fig. 2. a) Architecture of ELM b) use of ELM in neutral decoding.

The bulk of processing is done on the MLCP while simple digital functions are performed on the DSP. Compared to traditional designs that perform the decoding outside the implant, our envisioned system that provides opportunity for huge data compression by integrating the decoder in the implant. The MLCP is characterized by measurement. Integrating the neural decoding algorithm with the neural recording device is also desired to reduce the wireless data transmission rate.

III. PROPOSED SYSTEM

The below figure (3) shows the architecture of proposed system. Basically, The DSP only needs to send very simple control signals to the MLCP and performs the calculation of the second stage of ELM. The input to the MLCP comes from spike sorting that can be performed on theDSP.

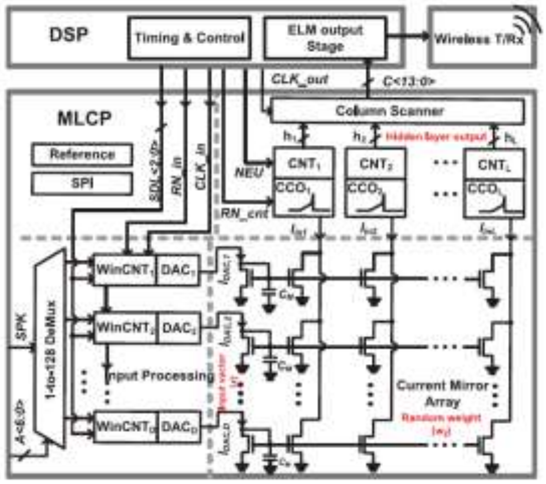

Fig. 3. Proposed system

Here high computation efficiency is achieved by exploiting fabrication mismatch abundantly found in analog devices. Since the number of computations in first stage far outnumbers those in the second stage. Up to 128 input channels and 128 hidden layer nodes are supported by the MLCP. On receiving a spike from the neural amplifier array the DSP sends a pulse to the DEMUX. Each row of the MLCP has a 6-bit window counter to count the total number of input spikes in a moving window.

The counter value in j-th row is converted into input feature current for the ELM. The delay length can be selected from among 5 delay steps ranging from 20 ms to 100

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ms.the input feature current from each row is further mirrored into all hidden-layer nodes by a current mirror array. Hence, ratiosof the current mirrors are essentially the input weights, and are inherently random due to fabrication mismatch of the transistors.

The hidden layer node is implemented by a current controlled oscillator (CCO) driving a 14-bit counter with a 3-bit programmable stop value to implement a saturating nonlinearity. The advantage of choosing this nonlinearity is that it can be digitally set and also some neurons can be configured to be linear. The output of CCO is a pulse frequency modulated signal with the frequency proportional to total input current. At last it can observe that this system reduces the effect of power supply variations.

IV. RESULTS

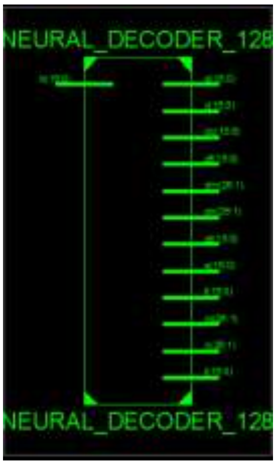

Fig.4. RTL Schematic

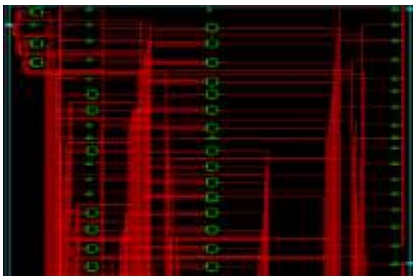

Fig. 5. Technology schematic

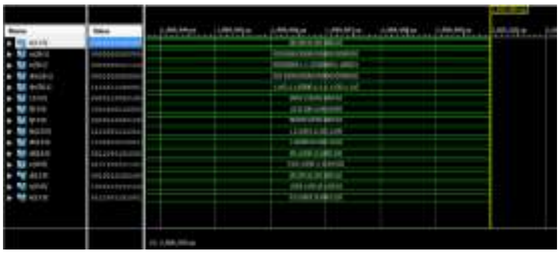

Fig. 6. Output

V.CONCLUSION

The proposed system achieves real-time motor intention decoding in an efficient way. The ELM algorithm used
In the decoder is quite general and has been shown to be a universal approximator. Higher dimensions of inputs and hidden layers can be handled by making a larger IC and also by reusing the same hidden layer several times. Higher input dimensions can be accommodated at same power by reducing the bias current input of the splitter DACs in input channels. So the proposed system gives effective results.

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