ASYNCHRONOUS BCI AND LOCAL NEURAL CLASSIFIERS

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Over the last years we have developed a portable BCI, called Adaptive Brain Interface (ABI), based on the on-line analysis of spontaneous EEG signals measured with a few scalp electrodes (6 to 9, normally 8) from which a local neural network classifier recognizes 3 different mental tasks. We have demonstrated publicly ABI on a number of occasions while subjects operated different brain-actuated applications, namely a virtual keyboard, a video game and a mobile platform (similar to a wheelchair).

ABI relies on an asynchronous protocol where the subject makes voluntary self-paced decisions on when to stop doing a mental task and start immediately the next one. This make the system very flexible and natural to operate, and yields rapid response times -- ABI tries to recognize what mental task the subject is concentrated on every 1/2 second. In this respect, every user chooses the mental tasks that he or she finds easier, and the preferred strategies to accomplish them. Subjects select three out of the following mental tasks "relax", imagination of "left" and "right" hand (or arm) movements, "cube rotation", "subtraction", and "word association".

Another characteristic of our approach is a mutual learning process where the user and the brain interface are coupled and adapt to each other. This accelerates the training process. The local neural classifier achieves error rates below 5% for 3 mental tasks, while correct recognition is 70% (or higher). In the remaining cases (around 20-25%), the classifier doesn't respond, since it considers the EEG samples as uncertain. The incorporation of rejection criteria to avoid making risky decisions is an important concern in BCI. From a practical point of view, a low classification error is a critical performance criterion for a BCI, for otherwise users would be frustrated and stop utilizing the interface. These classification rates (accuracy and error), together with the number of recognizable tasks and duration of the trials, yield a maximum transmission rate of approximately 2.0 bits/second. Normally, people reach the above-mentioned performances at the end of several days of moderate training (around 1/2 hour daily). But other subjects have also reached them in a single day of intense training. It is worth noting that one of these latter subjects is a physically impaired person suffering from spinal muscular atrophy. In total, we have worked with around 15 different subjects in a variety of conditions.

ABI has a simple local neural classifier where every unit represents an EEG prototype of one of the mental tasks to be recognized. We have found that this local network performs better than more sophisticated approaches such as support vector machines and temporal-processing neural networks (TDNN and Elman-like). This performance is achieved by simply averaging the outputs of the network for 8 consecutive EEG samples. The input to this classifier is the power spectrum in the band 8-30 Hz of each channel (standard fronto-centro-parietal locations) over the last second.

ABI is used to select letters from a virtual keyboard on a computer screen and write a message. For our trained subjects, it takes 22.0 seconds on average to select a letter. This time includes recovering from eventual errors. ABI also makes possible the continuous control of a mobile robot generating non-trivial trajectories among different rooms in a house-like environment. A key idea to control the robot with just 3 mental commands is to associate the user's mental tasks to high-level commands that the robot executes autonomously using the readings of its on-board sensors. Another critical aspect is that subjects can issue mental commands at any moment as ABI uses an asynchronous protocol. Experimental results show that mental control of the robot is only 35% longer than manual control.

CHALLENGES IN THE DEVELOPMENT OF A MINIATURIZED, SMART NEURO-PROSTHESIS SUITABLE FOR IMPLANTING INTO A BRAIN

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Passive microelectrode arrays have been widely used by researchers as a neuro-prosthetic tool to extract electrical signals from the brain. The microelectrode arrays are directly connected to measurement instruments through a large bundle of wires and are placed into the brain using surgical techniques. The large number of wires connected to current passive microelectrode arrays limits their widespread use as permanent neuro-prosthetic devices. In addition, there is an increasing demand for deploying microelectronics to develop a more sophisticated generation of neuro-prosthetic devices, capable of producing high quality electrical signals while significantly reducing the number of wires, or potentially eliminating wires entirely using an RF system.

To achieve this goal, a multiplexing electronic chip can be designed to multiplex the signal from each electrode in the array into a single channel; hence minimizing the number of wires exiting the electrode array. However, prior to multiplexing, individual amplifiers need to be added to each electrode at the array to enhance its signal to noise ratio. To that end, the chip can be designed with amplifiers arranged in geometrical patterns corresponding exactly with the electrodes of the array. Advanced assembly techniques can, in turn, be used to directly attach the chip to the passive microelectrode device. A wireless transmitter can be attached to the multiplex line, to transmit the signal from the brain through an RF link. The same RF link can also be used for powering the chip.

Features offered by a miniaturized device that combines analog electronics with the microelectrode array will come at a price. For one thing, power consumed by the active electronics will raise the temperature of the neuro-prosthetic device and could potentially destroy the neighboring biological tissue. And secondly, energy absorbed by the tissue because of the wireless features of the device (wireless coupling of power and wireless transmission of the signals to and from the implanted prosthesis) can be a potential source of long-term tissue damage.

The design of the electronics for the smart neuro-prosthesis is therefore constrained by micro-power levels that would prevent the excessive temperature rise (less than 1 deg centigrade) of the device and the choice of transmission frequencies that would minimize the absorption of radio frequency energy by the tissue. The signal to noise performance of traditional analog circuits is directly proportional to their operating power. To produce a high signal to noise ratio, non-traditional analog circuits solutions need to be developed.

The absorption of RF energy by the tissue is directly proportional to the increase in RF frequency. Minimizing the RF transmission frequency to reduce the energy absorption by the tissue will impact the transmission data rate. Hence, chip signal processing and data compression will need to be deployed to enhance the signal quality. Employing these functions in turn impacts the already small power budget and makes it even more difficult to develop a perfect neuro-prosthesis solution.