A Pliant Synaptic Network for Signal Analysis

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***ABSTRACT*:** Many complex systems can be monitored with multiple sensors, each of which produces a single time-varying output. One example of such a system is the human body when it is monitored with surface electrodes for EEG or EKG readings. To interpret the readings a doctor often looks for waveform "signatures." These signatures are usually easily detectable with Artificial Neural Networks (ANN). This paper describes a computer program that automatically creates an ANN to detect user-selected signatures. When the user of the program is satisfied with the performance of the ANN, the ANN parameters can be downloaded directly onto a chip that becomes part of a hardware package for monitoring the system. For example, some types of epileptic seizures can be recognized by their characteristic signatures. This program will allow medical doctors to identify targets, then construct an ANN to recognize the target signature, test the ANN, and download the ANN to a chip that can be implanted with electrodes to monitor the patient. The basic techniques in this program have wide applications both inside the medical field (e.g., EKG and MEG) and in non-medical applications (e.g., seismology and factory control).

***Keywords*:** Signal Processing, EEG, EKG, ASIC, Synaptic Networks

Introduction

Neural networks are interconnected systems of simple units each of which combines several inputs into one output. This remarkably simple architectural paradigm is the basis of nervous systems and brains throughout the animal kingdom. It is also the basis of the emerging discipline of Artificial Neural Networks (ANN).

Artificial Neural Networks have successfully solved a number of problems that were intractable when using more conventional computational methods. Neural networks (biological and artificial) have the ability to operate with incomplete or noisy information. Neural networks are not controlled by a program, but correctly translate inputs to outputs when trained with a significant number of examples.

The particular type of ANN that is used here is the synaptic net, which is often described as "neural networks without the neurons." Synaptic nets are easy to implement in hardware, especially the hardware used here: the Application Specific Integrated Circuit (ASIC). Synaptic nets also have the desirable characteristic that (in simple cases) they can be constructed from target patterns in such a way that training is unnecessary.

Synaptic nets retain only the synapses and the interconnection topology. Taking the neurons out of the net removes many of the problems but only one of the strengths: nonlinearity. Synaptic nets are very simple, but quite powerful. Combinations of synaptic nets can approximate the behavior of neural nets to any precision desired, just as digital audio signals can approximate analog audio signals to any precision desired.

The Target-driven Synaptic Net

The simplest synaptic net for processing patterns of length n is a vector w of length n. The evaluation of pattern p1 by w is just the inner (dot) product of p1 and w (written p1*w). A simple update rule would be to add some scalar multiple of p (i.e. αp) to w such that the dot product of p and the updated w (i.e. $w + \alpha p$) would have zero error.

This α is easy to find. If the target is t and the actual value of p * w is v, then

$$t = p * (w + \alpha p) = p * w + \alpha(p * p) = v + \alpha p^2 \quad \text{so} \quad \alpha = \frac{t - v}{p^2}$$

In neural network terms, this system would be a perceptron with no bias, no transfer function, and a changing learning constant. In synaptic net terms this system is a flat real-valued synaptic net.

If all vectors are normal (in the sense that for all vectors X, X * X = 1) and the target for vector V is 1 then the synaptic net that recognizes V is equal to the vector V. Every other (normal) vector will yield a value less than 1 when dotted with the fully trained synaptic net. Furthermore, the closer a vector is to the net (in Hamming distance), the nearer the dotted product will be to 1.

The normality of the vector space is insured by the simple fiat of normalizing each input vector. This is easily accomplished by dividing each element of a vector by the square root of the dot product of the vector with itself. The vectors that are being normalized are continuous segments of the input waveforms (Figure 1).

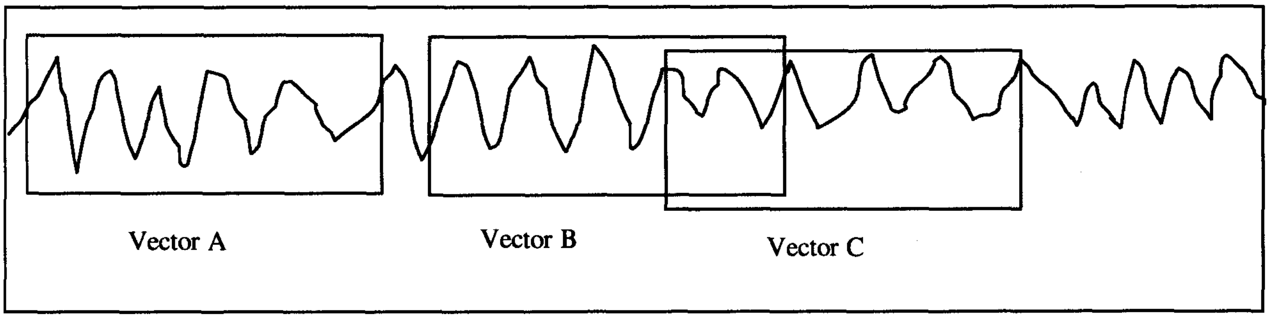

Figure 1: The input vectors are just overlapping segments of the waveform

The SNAP Program

The Simple to use Network to ASIC Program (SNAP) allows the user to construct, test, refine, and download the target recognition synaptic networks. The example given here is for EEG data, but the program is readily applicable to any complex system that is monitored by a collection of synchronized sensors and where a simple signature is the target.

A typical commercially available EEG analysis program will record the output of a number of surface electrodes onto a magnetic disk. The magnetic disk is then inserted into a standard PC and the analysis program shows the electrode outputs as several parallel waveforms (Figure 2). Each waveform is the output of one electrode and the entire electrode trace is typically too large to see at one time. Hence the representation is only a window that can be moved along the entire set of waveforms.

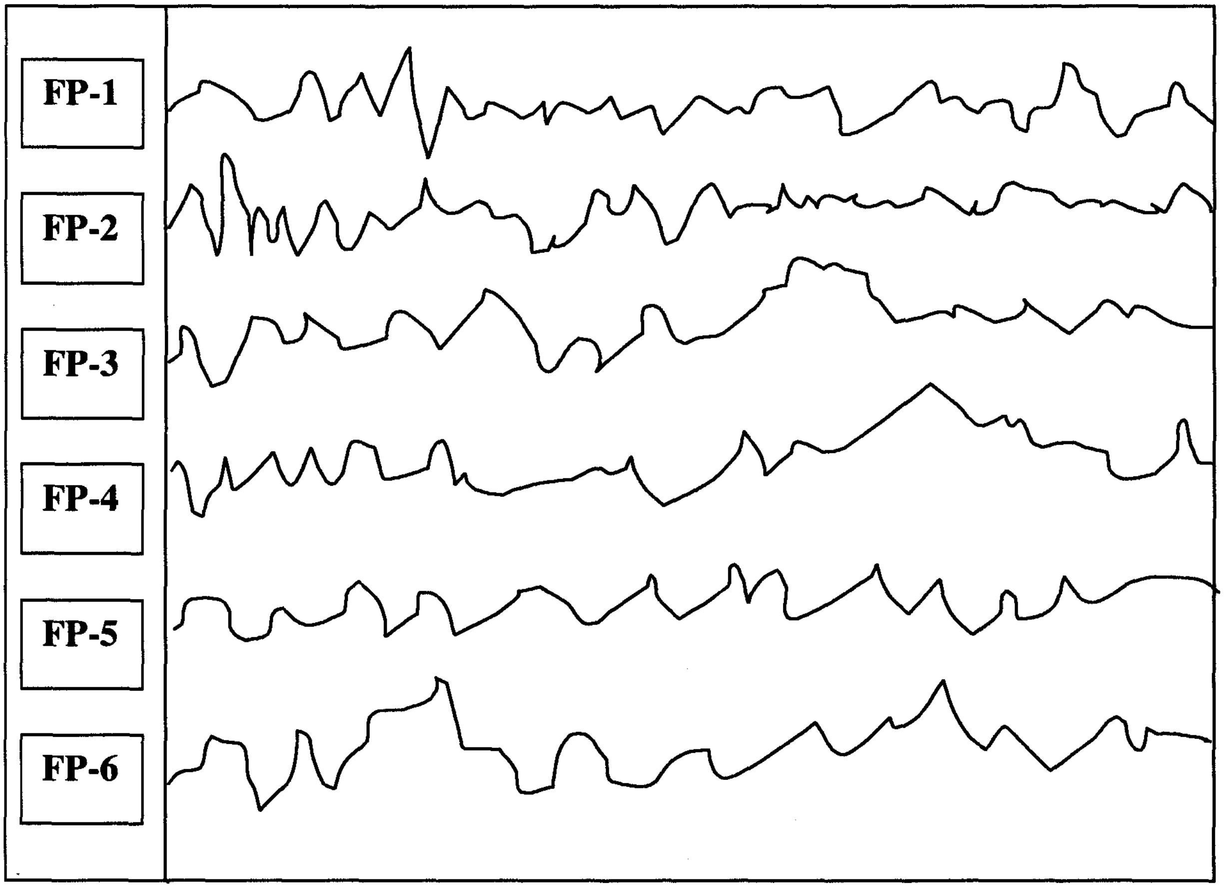

Figure 2: A typical PC representation of EEG electrode outputs

For example, a doctor may select an area that has a signature indicating the onset of seizure. The SNAP program uses this information to build a software ANN that recognizes this target (Figure 3). The doctor then tests this ANN simulation on the other parts of the data, looking for both false positives and false negatives. If the ANN performs correctly, a new ANN that is synthesized with fewer electrodes is tried. When a proper ANN is synthesized (with the minimum number of electrodes) the information is downloaded via an RS-232 connection to an ASIC that has been especially designed for this purpose. The ANN ASIC is now implanted in the patient and the electrodes are connected. The implanted system can now reliably detect the onset of seizure and alert attendants.

There is an enhancement of the ANN builder that allows much greater generality in signature recognition, viz. more than one target can be selected. This creates a larger ANN that will recognize several variations of the target condition.

If two targets are selected the ANN is constructive in Conjunctive Normal Form. For example, if electrodes 1, 4, and 5 from segment #1 (points 100 to 150) are one version of the target and electrodes 3 and 7 from segment #2 (points 350 to 420) are another version of the target then the effective target is:

Target = ((segment1, electrode 1) and (segment1, electrode 4) and (segment1, electrode 5))
or ((segment2, electrode 3) and (segment21, electrode 7))

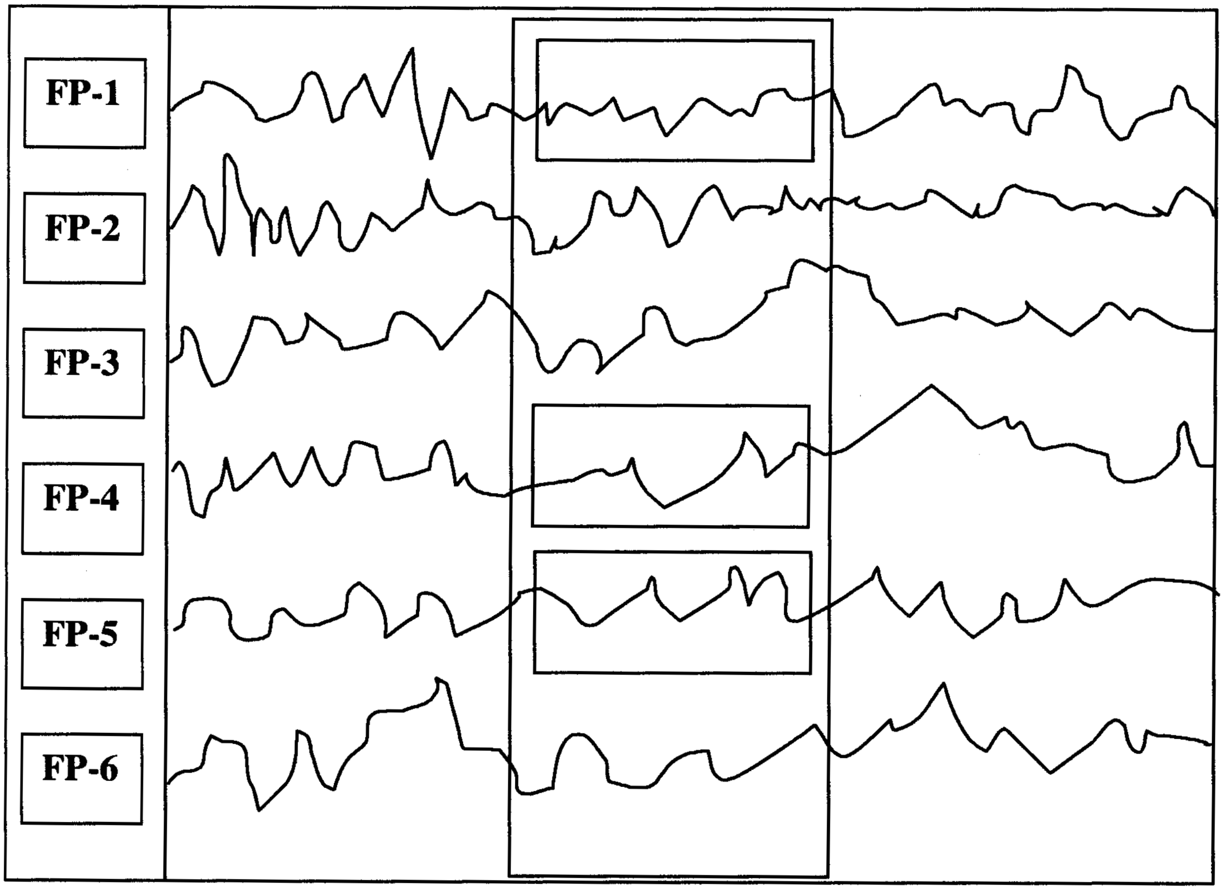

Figure 3: A Target is selected (Electrodes 1, 4, and 5 only)

Summary

Here is a step-by-step breakdown of the user process of hardware configuration with SNAP. The EEG seizure detection example is used but the process is easy to generalize:

1. Attach electrodes and make a multi-channel recording onto JAZ disk.
2. View the recording using the SNAP display. Select targets and build the software ANN.
3. Test the software ANN on entire data set or on other data sets. Find the minimum ANN.
4. Download weights from software ANN into weight registers of ASIC.
5. Implant ASIC and electrodes. (Minimize number of electrodes, avoid noisome electrodes)
6. Perform in vivo testing.

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