

# Pulsed Neural Networks:

Temporal Signal Processing Using Artificial Neural Networks with Dynamic Synapses

*CYSF 2000 Report*

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## Table of Contents

<i>Table of Contents</i>	2
<b>1. Abstract</b>	<b>3</b>
<b>2. Introduction</b>	<b>4</b>
<b>3. Objective</b>	<b>5</b>
<b>4. Background</b>	<b>6</b>
<b>4.1. The Nervous System</b>	<b>6</b>
<b>4.2. Information Representation and Processing in Cells</b>	<b>7</b>
4.2.1. Electrical Properties	8
4.2.2. Chemical Synapses	9
4.2.3. Neurotransmitters	10
4.2.4. Coding Systems	10
4.2.5. Synaptic Plasticity	11
<b>4.3. Artificial Neural Networks</b>	<b>12</b>
<b>5. Methods</b>	<b>13</b>
<b>5.1. The Dynamic Synapse Model</b>	<b>13</b>
<b>6. Results</b>	<b>18</b>
<b>7. Discussion</b>	<b>21</b>
<b>7.1. Computational Complexity</b>	<b>23</b>
<b>8. Applications</b>	<b>23</b>
<b>9. Conclusion</b>	<b>25</b>
<b>10. Acknowledgements</b>	<b>27</b>
<b>11. References</b>	<b>28</b>

## 1. Abstract

Artificial neural networks (ANNs) are computational abstractions which enable computer systems to perform tasks which would otherwise be impossible, since, in some instances, statistical rules can not be determined by traditional methods. Pattern matching and classification are main applications of ANNs. Modeling the human brain in function, ANNs consist of a number of nodes interconnected by “weights” (analogous to biological synapses) which are adjusted in a process termed “learning.” These neurons form a variably interconnected grid whose spatial properties are determined by the weights of the network. Information is stored in, and processed by the spatial patterns of the network. However, temporal signals are an important form of input and time-series such as sound waveforms can traditionally not be effectively converted into spatial representations. Attempts to perform temporal to spatial transformations in ANNs has generally required a combination of non-ANN preprocessing, very large numbers of neurons and modifications to the network structure which are unsubstantiated by biological research.

The latest neurobiological findings indicate that synaptic connection weights are dependent on the history of activation of every particular synapse. This phenomenon is termed synaptic plasticity and is now believed to be an integral part of the computational mechanism of biological neural networks. In this paper it is demonstrated that a small artificial neural network interconnected with dynamic synapses is capable of performing rudimentary temporal to spatial transformation. Simple networks connected using dynamic synapses have proved able to convert simple temporal patterns into spatial ones. This may provide a critical first step in creating powerful biologically realistic and computationally efficient neural networks for signal processing. Applications are presented including speech recognition, noise reduction and blind-signal separation.

## 2. Introduction

Traditional artificial neural network models exchange continuous variables between neurons (McCulloch and Pitts, 1943). This paradigm was based on some of the earliest neurobiological research (Hodgkin and Huxley, 1939), and has been used for many applications. However, recent biological research has found that networks do not communicate by this method, but rather by sequences of pulses. See (Kandel and Schwartz, 1991) for a review. The use of timing between pulses and average pulse rate as a notation for internal data representation has stimulated much research in the field of artificial pulsed neural networks. Detailed biologically realistic models of individual neurons have been developed to help understand the way that computation works within living organisms. Early steps have been taken to explore the use of these more accurate models to perform a variety of tasks far better than traditional neural networks and statistical techniques (Liaw and Berger, 1996). Recent discoveries suggest that synapses are very important in computation and do not have fixed weights, but are instead dynamic, their efficacy depending on the short- and long-term history of their activation. The implication is that neural networks with dynamic synapses may be particularly well suited to perform various signal-processing operations on time-series.

### 3. Objective

Wang and Alkon proposed a complex multi-layer with a system of time-delays to convert temporal signals into a spatial pattern (Wang and Alkon, 1993). However, this method took hundreds of interconnected neurons and its biological realism is unsupported by recent research. Buonomano and Merzenich showed that a 500 neuron neural network with elaborate neuronal properties could transform the time interval between two pulses into a spatial pattern (Buonomano and Merzenich, 1995). The purpose of this project is to show experimentally that neural networks with dynamic synapses exhibit temporal to spatial conversion capabilities which make them well suited to process digital signals. A key element is investigating whether it is possible to produce similar results to those of the Wang-Alkon and Buonomano-Merzenich neural networks using a smaller network with dynamic synapses in a fashion that is both more biologically realistic and computationally efficient. With this property explored, the goal is to apply these networks with dynamic synapses to perform signal processing operations in methods analogous to those present in the brain.

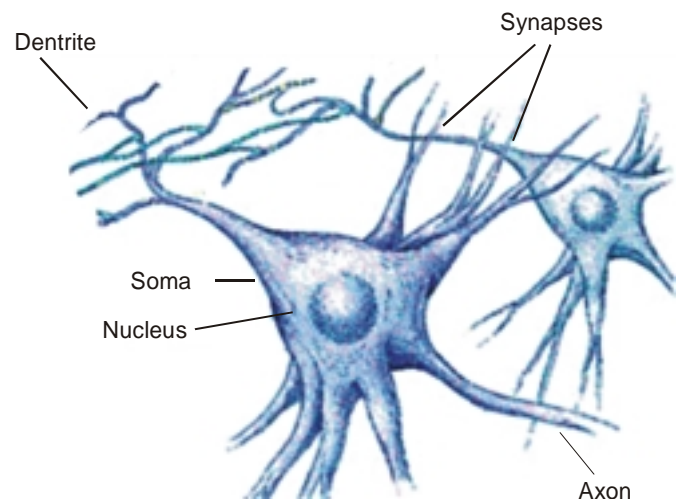
## 4. Background

In order to construct neural network models which exhibit similar properties to biological systems, and are therefore capable of processing information in a similar fashion to biological organisms, some background in the neurobiology of computation is necessary.

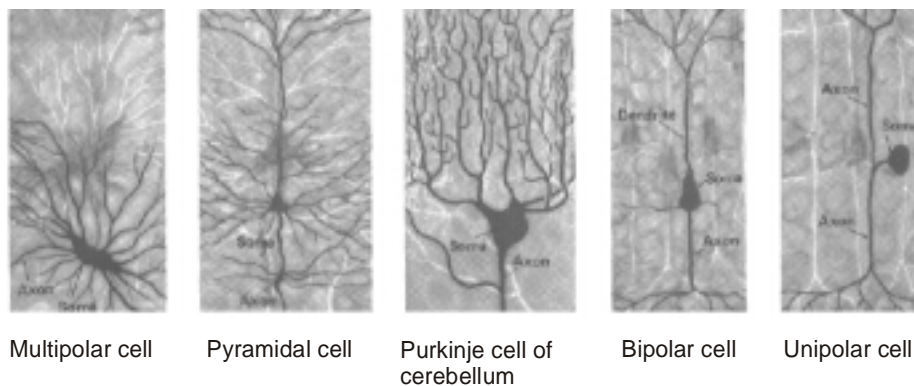
### 4.1. The Nervous System

Our knowledge of the nervous system has been developed largely since the late 19<sup>th</sup> century. Before then, it was uncertain that cell theory applied to the brain at all. In 1873, Camillo Golgi of Italy discovered a method of dyeing only select neurons in brain tissue, making their structures clearly visible. However, this method was not put to extensive use until the Spanish histologist Santiago Ramón y Cajal stumbled upon the

method while working in a small laboratory in Barcelona in 1888. After this momentous date, he worked feverishly, applying the Golgi technique to many areas of the nervous system. Most importantly, he realised that the entire cell was dyed by the process and that nerve cells existed as independent entities (Cajal, 1934). The research suggested that neural connectivity was "contiguous", not "continuous." Thus, synapses were necessary to connect between neurons.



**Figure 1** Artist's rendition of a neuron, the structure of which Ramón y Cajal discovered in 1888. This diagram is named using modern terminology.



Multipolar cell    Pyramidal cell    Purkinje cell of cerebellum    Bipolar cell    Unipolar cell

**Figure 2** There are many types of nerve cells within the central and peripheral nervous systems with different cell morphologies. Yet they share the same general features which are responsible for their functioning. (Adapted from Cajal, 1934)

## 4.2. Information Representation and Processing in Cells

The body of knowledge regarding how cells process information was not developed until the 1940s (Shannon and Weaver, 1948).

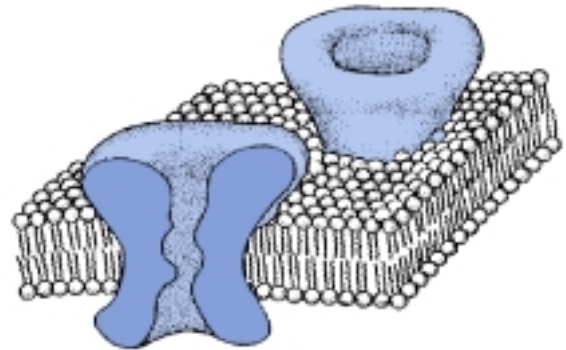
This was followed up by marvelously thorough single-cell physiology studies by Hodgkin, Huxley, Katz and Eccles (Hodgkin and Huxley, 1939) which revealed, for the first time, the electrical behavior of neurons. Electron microscopy enabled the viewing of synapses and neuron fine structure. More importantly, the novel experimental techniques of using intracellular capillary electrodes and subsequently space and voltage clamps enabled them to make precise recordings of electrical signals of cell activity. (Bower and Beeman, 1998).

Nerve cells use two different methods for information storage and transmission, one chemical, the other electrical. While electrical synapses do exist, they will not be considered here, as they are not generally modeled in artificial neural networks. Instead, the electrical state of a neuron will be considered as its internal information storage mechanism, and chemical synaptic transmission as its method for communicating with other neurons.

Processing of information in the cellular matrix of the brain is thought to occur through the following basic process. Information enters the brain through neurons associated with the sensory system. These are then connected to processing neurons. A neuron functions by taking



**Figure 3** An affectionate view of the modern neurobiologist with his trusty microelectrode (From Kuffler, 1958)



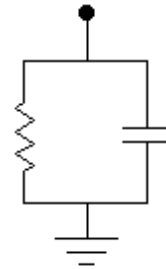
**Figure 4** The lipid membrane of neuron cell walls contains proteins which selectively facilitate ion diffusion, causing a potential difference to be created.

the weighted sum of its input and their associated weights. These weights are determined by learning. If the value of the weighted sum of these exceeds a certain threshold, the neuron fires.

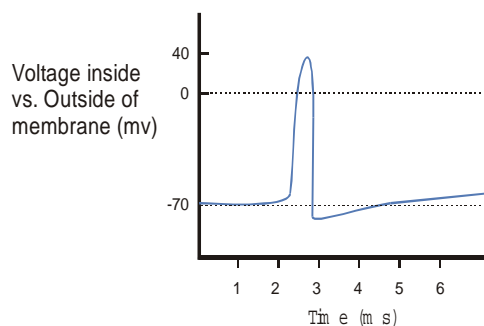
#### 4.2.1. Electrical Properties

Like any cell in the human body, there is a potential difference between the nucleus of the cell in the extra cellular fluid. The electrical state of a neuron is regulated by ion channels which selectively facilitate diffusion of  $\text{Ca}^{2+}$ ,  $\text{Na}^+$ ,  $\text{K}^+$  and other ions into and out of the cell (see Figure 4). Ion transfer results in the creation of a potential difference between the inside and the outside of the cell, as shown in Figure 6. This charge separation is responsible for the so called membrane potential. It is positively charged on the outside and negatively charged on the inside. Because the inside of the neuron is negative to the outside, and we arbitrarily define the extra cellular fluid to have a charge of zero, the resting potential is negative,

generally between -40 and -75mV. This is significant because in one way or another, all signaling involves a change in this membrane potential. The overall effect of active and passive ion channels, the cell may be considered as the RC circuit shown in Figure 5. For more complex models, the neuron may be modeled as a system of interconnected compartments each with their own RC properties, however, these compartmental models are beyond the scope of this investigation since they are computationally prohibitive for ANNs designed to solve problems.



**Figure 5** Schematic representation of a neuron. The potential difference across the membrane creates capacitance. And the neuron acts as an RC circuit



**Figure 6** A typical action potential recorded across the membrane of a neuronal axon, much like those discovered by Hodgkin and Huxley in the giant squid.

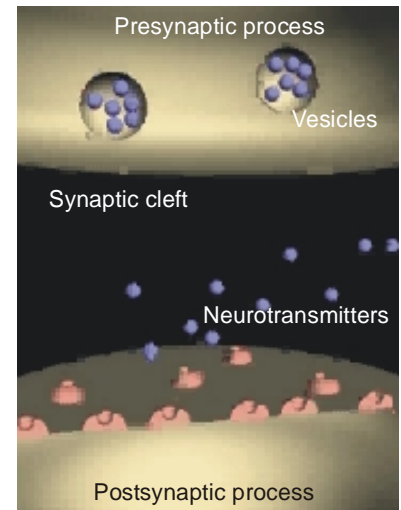
The electrical state of the cell determines when it will signal, through either chemical or electrical synapses, activity to neighboring neurons. Generally, this is modeled as a hard-limited threshold, that is, a certain value which, if the resting potential of the neuron exceeds it, will cause the cell to fire an output signal. This output signal is called an *action potential* (see Figure 6).

#### 4.2.2. Chemical Synapses

Chemical synapses consist of two membranes on adjacent neurons, separated by the synaptic cleft. They are the method of communicating information between cells. The mechanism consists of three parts. One is the presynaptic cell process which governs the release of neurotransmitter signals. The postsynaptic process is the part of the system in which neurotransmitters are received by the second neuron. Intervening between these two processes is the synaptic cleft, a gap of approximately 20nm across which messages must travel. In order to carry information across this distance, presynaptic processes release

neurotransmitters in the form of vesicles. Vesicles, in the words of neuroscience scholar Sanford Palay, are like fine chocolates, coming in a variety of shapes and sizes, and packed with different kinds of filling (Palay, 1958). These small membrane bounded globules of neurotransmitter are the vehicle of chemical signaling in the nervous system.

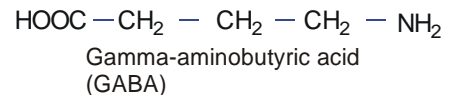
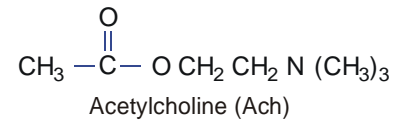
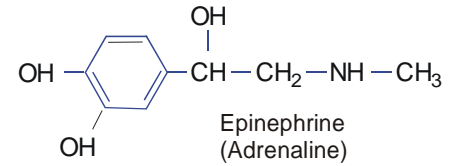
Neurotransmitter release is stimulated by the internal potential of the cell exceeding a certain value. Recent characterizations of vesicle release behavior have indicated that the process is both quantal and probabilistic. Quantal because a neurotransmitter vesicle is either released or it is not at a given time (see Figure 9), and probabilistic because given an electrical stimulus, the probability of release is generally only between 10% and 30%. As will be shown later, these factors form the basis for pulsed neural networks.



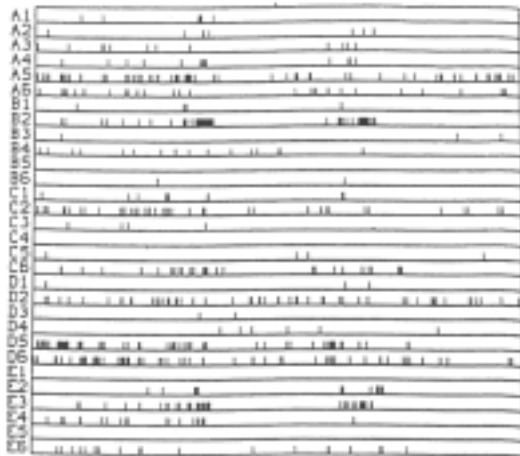
**Figure 7** A model chemical synapse. Neurotransmitter filled vesicles accumulate on one side of the synaptic cleft and are transferred to the other given an electrical stimulus.

### 4.2.3. Neurotransmitters

Neurotransmitters signal the postsynaptic neuron to activate. There exist many types of neurotransmitters, which fall into two major types: inhibitory and excitatory. Excitatory neurotransmitters cause an increase in the probability of postsynaptic neuron activation, while inhibitory neurotransmitters cause a decrease in the probability of postsynaptic neuron activation. The most important excitatory neurotransmitter is acetylcholine (ACh), and the most commonly studied inhibitory neurotransmitter is  $\gamma$ -aminobutyric acid (GABA). As well, norepinephrine, epinephrine and a variety of other amino acids, amines and peptides have been shown to act as transmitters with either excitatory or inhibitory effects in a wide variety of neurons.



**Figure 8** Neurotransmitters (above) are organic molecules which are released by presynaptic neurons and act to signal the postsynaptic neuron. Both excitatory (epinephrine and acetylcholine) and inhibitory neurotransmitter structures (GABA) are shown.



**Figure 9** An example of spike trains in biological neurons. 30 neurons labeled A1 through E6 on the vertical axis and spikes are indicated as vertical lines at certain points of time along the horizontal axis which represents 4000ms. From (Kruger and Aiple, 1988)

### 4.2.4. Coding Systems

Despite a wealth of research in the field, the method by which information is encoded in spike trains remains unclear. Two popular hypotheses are *rate coding*, also called *frequency coding*, which assert that the average rate of firing of the neuron carries the information content of the spike train, and *temporal coding*, in which the temporal structure of the pulses in the spike train contain the information. It has been known for some time that spike trains contain very large amounts of information. While temporal coding methods have the capability of containing more information than rate coding methods, the problem arises when noise is introduced into the system. Biophysical observations have indicated that there is noise in spike trains. However, it remains unclear as to

whether this noise may actually contain statistically relevant information (Liaw and Berger, 1996).

#### 4.2.5. Synaptic Plasticity

The dynamic synapse model, which considers synaptic efficacy to be dependent on the synapse's immediate and long term history, is supported by biological research. In biological neurons, facilitation and depression both occur on many time scales. On the longest time scales, with which we are quite familiar, we believe that learning occurs when certain synaptic connections are strengthened and others weakened. The Hebbian theory of learning (Hebb, 1949) asserts that correlated activity of pre- and postsynaptic cells strengthens the synaptic connection between them. This is referred to as long-term potentiation (LTP), and is the subject of a great deal of research. In much shorter time frames, the response to the second of a pair of neuronal impulses may be either weaker or stronger than the first depending on synapse dynamics. In paired-pulse facilitation (PPF) the second pulse is more effective than the first. Similarly, post-tetanic potentiation, which results from very strong bursts of neural activity, causes subsequent neural impulses to have a greater probability of causing neurotransmitter release. In other cases, paired-pulse depression (PPD) occurs, causing a decreased probability of neurotransmitter release with the second impulse. As discussed below, these properties markedly improve the computational power of artificial neurons which have synapses that are dependent on their immediate and long term history.

**Table 1** *Facilitative and depressive plasticity phenomena at varying time scales.*

Phenomenon	Duration	Locus of Induction
<i>Short-term Enhancement</i>		
Paired-pulse facilitation (PPF)	100ms	Presynaptic
Augmentation	10s	Presynaptic
Post-tetanic potentiation (PTP)	1 minute	Presynaptic
<i>Long-term Enhancement</i>		
Short-term potentiation (STP)	15 minutes	Postsynaptic
Long-term potentiation (LTP)	>30 minutes	Presynaptic and Postsynaptic
<i>Depression</i>		
Paired-pulse depression (PPD)	100ms	Presynaptic
Depletion	10s	Presynaptic
Long-term Depressions (LTD)	>30minutes	Presynaptic and Postsynaptic

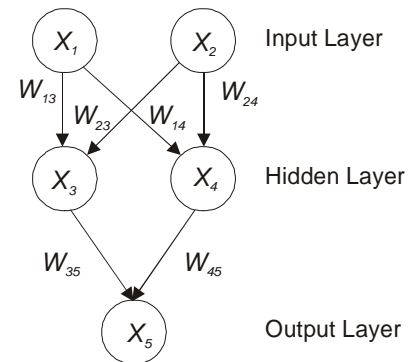
Adapted from (Koch, 1999)

### 4.3. Artificial Neural Networks

In the 1940s, McCulloch and Pitts (McCulloch and Pitts, 1943) published a landmark paper which proposed that a network of neuron-like objects could act as a general computer, a Turing machine. Their basic model operated using discrete time steps by the following procedure:

*For each neuron, if, at the last time step, I received at least  $T$  units of charge, then fire 1 unit to every neuron I'm connected to.*

This is known as the threshold gate model, for the threshold which determines whether a neuron will fire with a given input. All of the neurons in the network are interconnected with certain weights, much as the interconnections in the brain have a certain efficacy. In this model, the value  $X_i$  represents the internal activation energy of a neuron  $i$  at any given point in time. Any pair of connected neurons  $i$  and  $j$  are connected by the "weight"  $W_{ij}$ . The network multiplies each input by its respective weight and sums these values. In the McCulloch and Pitts model, the neuron  $X_m$  is activated if the value  $\sum_{i=1}^n x_i w_{im}$  is above some threshold. In more refined neural network models, this hard-limited threshold has been replaced with a transfer function  $g(x)$  which is often a sigmoidal logistic function.



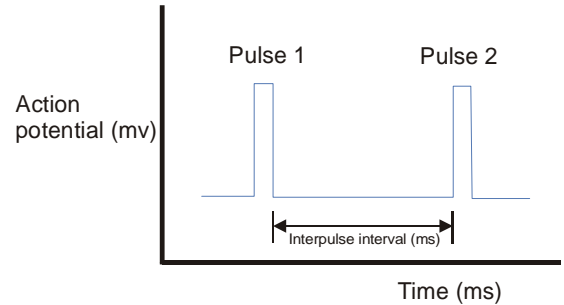
**Figure 10** An artificial neural network model. Each neuron has a value of  $X_i$  which represents its level of excitation (analogous to action potential). Arbitrary pairs of neurons  $i$  and  $j$  are interconnected by the weight  $W_{ij}$ .

These models use continuous real-valued parameters for  $X_i$  and  $W_{ij}$ . However, studies on individual biological neurons indicate that synapses operate in a binary fashion. Either they are activated or they are not (see Chemical Synapses). The continuous valued curves are only valid when we consider the average activity over populations, and not for individual neurons. Furthermore, this model generally assumes  $W_{ij}$  to be constant over the processing time scale (although it may change because of LTP.) As shown above, though, biological synapse dynamics are dependent on facilitation and

depression on multiple time scales from milliseconds (PPF/PPD) to lifetimes (LTP/LTD). This discrepancy between traditional neural network models and recent biological research has led researchers to explore the possibility of using pulsed neural networks, ones which operate on spike trains and which use dynamic synapses for computation.

## 5. Methods

In this project, a neural network was developed with the objective of converting a temporal pattern into a spatial one. More specifically, it converts pairs of pulses with various inter pulse intervals (see Figure 11) into unique spatial patterns. In order to do this a network with one input neuron, five neurons in the hidden layer, and one output was developed. The input neuron was connected to the hidden layer by one dynamic synapse per neuron. While advanced neural network modeling packages such as GENESIS exist, algorithms to model dynamic synapses have not yet been implemented in these programs. Therefore, this network was developed in C, using only standard libraries.



**Figure 11** A pulse pair showing the inter pulse interval

### 5.1. The Dynamic Synapse Model

For the purposes of this model, let the spike train be represented by  $\{t_1 < t_2 < t_3 \dots t_n\} \in \underline{t}$  where  $t_i$  represents the timing of a pulse in the spike train. The synapse operates so as to generate the sequence  $S(\underline{t})$  which contains elements  $t_i$  for each spike  $t_i \in \underline{t}$  that results in the release of a neurotransmitter vesicle.

The probability of the release of a neurotransmitter vesicle from a synapse is given by:

$$p_s(t_i) = 1 - e^{-C(t_i)V(t_i)}$$

where:

$p_s(t_i)$  is the probability that the  $i^{\text{th}}$  spike in a presynaptic spike train triggers the release of a vesicle at time  $t_i$  at synapse  $S$ .

$C(t) \geq 0$  describes the state of facilitation of the synapse at time  $t$ .

$V(t) \geq 0$  describes the state of depletion of the synapse at time  $t$ .

The dynamics of facilitation are given by:

$$C(t) = C_0 + \sum_{t_i < t} c(t - t_i)$$

where  $C_0$  is a parameter that can be related, for example, to the resting concentration of calcium ions in the synapse. The function  $c(s)$  models the response  $C(t)$  to a presynaptic spike that reached the synapse at time:  $t - s$  by the exponential decay function:

$$c(s) = \alpha \cdot e^{-s/\tau_c}$$

where:

$s$  is the length of time elapsed since the synapse firing impulse  $t_i$

$\alpha$  is the magnitude of the response, and

$\tau_c$  is the decay constant of the response

This function models, in an abstract way, synaptic processes which result in facilitation. The form of the equation for  $c(s)$  could arise if, for example, presynaptic calcium dynamics were governed by some sort of first order process (Maass and Zador, 1998b).

The dynamics of depletion are given by:

$$V(t) = \max\left(0, V_0 - \sum_{t_i: t_i \in \mathcal{S}(t)} v(t - t_i)\right)$$

The value of  $V(t)$  represents the extent to which the neurotransmitters at a particular synaptic junction have been depleted, and thus depends on the subset of  $t_i \in \underline{t}$ ,  $t_i < t$ . The function

$v(s) = e^{-s/\tau_v}$  is analogous to the equation for facilitation decay, but with a different decay constant.

The neuron model used is as follows:

For a network with 1 input neuron (ie: all hidden neurons receive the same input),  $h$  neurons in the hidden layer and  $n$  neurons in the output layer,

$$y_i(t) = \theta(Y_i(t)) \text{ with } Y_i(t) = \sum_S w_{is} P_{is}(t) x(t)$$

where the sum is taken over the  $S$  different synapses between the input and hidden unit  $i$  and

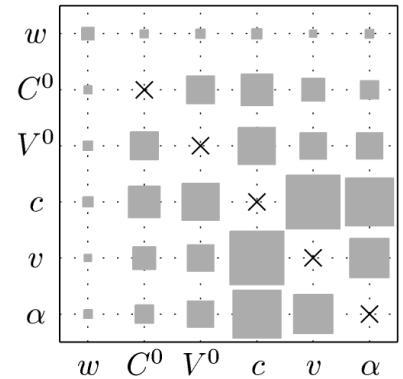
$x(t)$  is the input spike signal to the network.  $\theta$  denotes the sigmoid function  $\theta(x) = \frac{1}{1 + e^{-x}}$ .

To train a "neural network" of these neurons, the five hidden parameters,  $C_0, V_0, \tau_c, \tau_v, \alpha$  may be adjusted. The effectiveness of this in processing time-series to perform curve fitting has been demonstrated by (Zador et al., 1998).

In order to "train" the network, each of the five hidden neurons had its synapse's parameters adjusted so that it would fire with maximal probability on the second spike of a pulse-pair with a certain inter pulse interval. Each neuron was trained with ideal release properties at one of 20ms, 40ms, 60ms, 80ms or 100ms (see Figure 10). Because training algorithms have not been developed for networks of dynamic synapses, a brute force gradient-descent method was used. Parameters were selected from the following

intervals:  $C_0 \in [0.1, 1]^1$ ,

$V_0 \in [0.1, 3], \tau_c \in [1, 99]^2, \tau_v \in [1, 99], \alpha \in [0, 1]^3$  in order to maximize



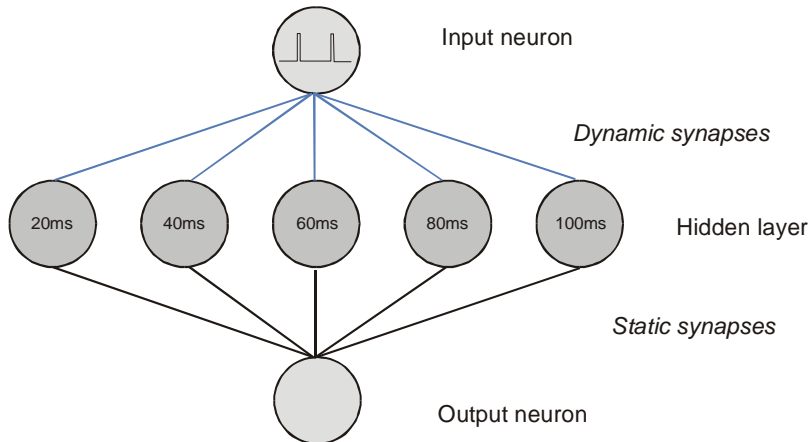
**Figure 12** The effectiveness of various synaptic parameter pairs on reducing error between the output of a neural network and the desired output. Smaller squares indicate less error and thus a better choice of parameters to manipulate. (From Zador, Natschläger and Moos, 2000)

<sup>1</sup> It was observed that if the parameter range was  $C_0 \in [0, 1]$ , that  $C_0$  would always assume a value of 0.

However, this resulted in decreased contrast between the output to the desired inter pulse interval and inter pulse intervals for which "neurotransmitter release" was not desired.

<sup>2</sup>  $\tau_c$  exceeded its maximum value by the time the pulse interval reached 40ms. When the range was expanded to  $\tau_c \in [1, 10000]$ , the same occurred. Therefore, it appears that the brute force approach to setting  $\tau_c$  is ineffective.

the neuron response to the second pulse in a pulse pair with the desired inter pulse interval, and minimize response to other inter pulse intervals. The parameters which were determined are shown in Table 2.



**Figure 13** The neural network model used in this project. The pulse pair is applied to the input neuron that is connected to five hidden neurons by dynamic synapses. Each hidden neuron has been trained to fire with greatest probability at a certain centre frequency. Connections to the output neuron are static

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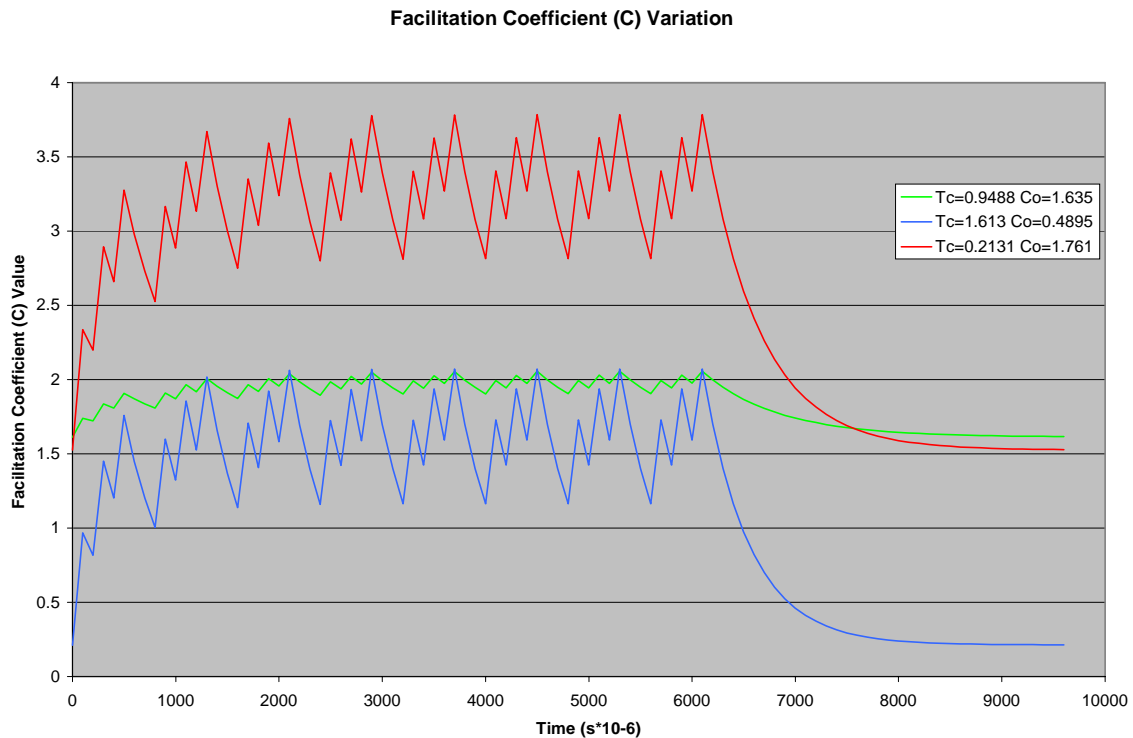
<sup>3</sup> Increasing the range to  $\alpha \in [0,10]$  was attempted, even though this decreases the biological realism of the model since, strictly defined,  $\alpha$  is a percentage. However, when this was attempted, this resulted in decreased contrast between the output to the desired inter pulse interval, and the inter pulse intervals for which "neurotransmitter release" was not desired.

**Table 2** *Neuron parameters determined using brute force training algorithm*

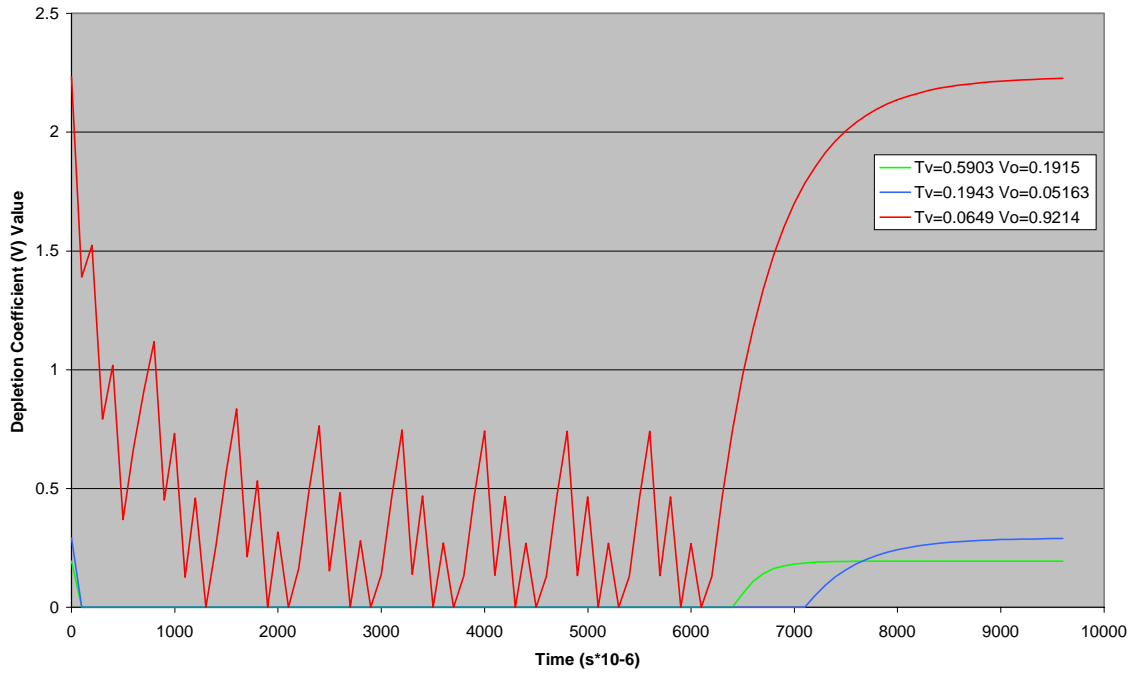
Neuron Number	Inter pulse interval trained at (ms):	$C_0$	$V_0$	$\tau_C$ (ms)	$\tau_V$ (ms)	$\alpha$
1	20	0.1	1.0	37.0	3.0	0.9
2	40	0.1	0.5	99.0	13.0	0.9
3	60	0.1	0.5	99.0	25.0	0.9
4	80	0.1	0.5	99.0	39.0	0.5
5	100	0.1	0.4	99.0	45.0	0.9

## 6. Results

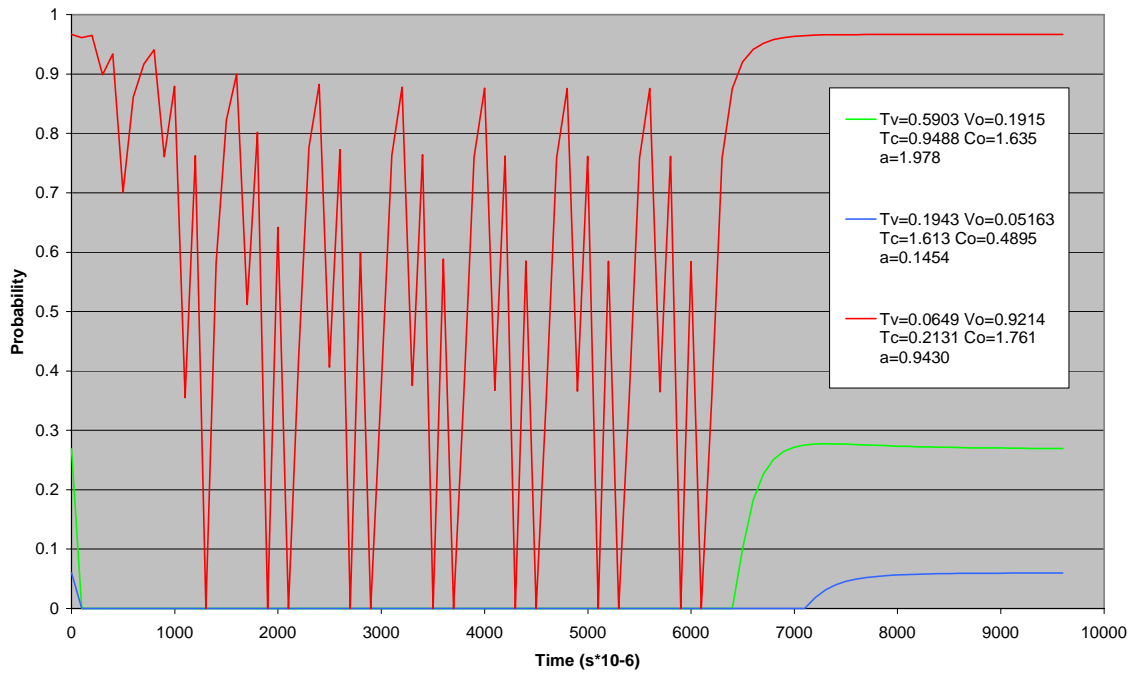
In order to demonstrate the characteristics of a neural network with dynamic synapses, data was collected from the network constructed for this project to indicate the variations in synapse parameters over time. In this example, the input to the network was a burst of 3 spikes at  $200\text{E-}6\text{s}$  intervals, followed by a  $400\text{E-}6\text{s}$  recovery period. We can see that this has significant effects across the time interval shown. Depending on the values of the depletion coefficients, the neurons may have zero response to the second pulse, as they have been completely depleted of the hypothetical neurotransmitter. For the first few impulses, the facilitation coefficient increases, but hits a maximum after the second set of 3 spikes. These features are significant, as they lay the framework for temporal selectivity in the next section.



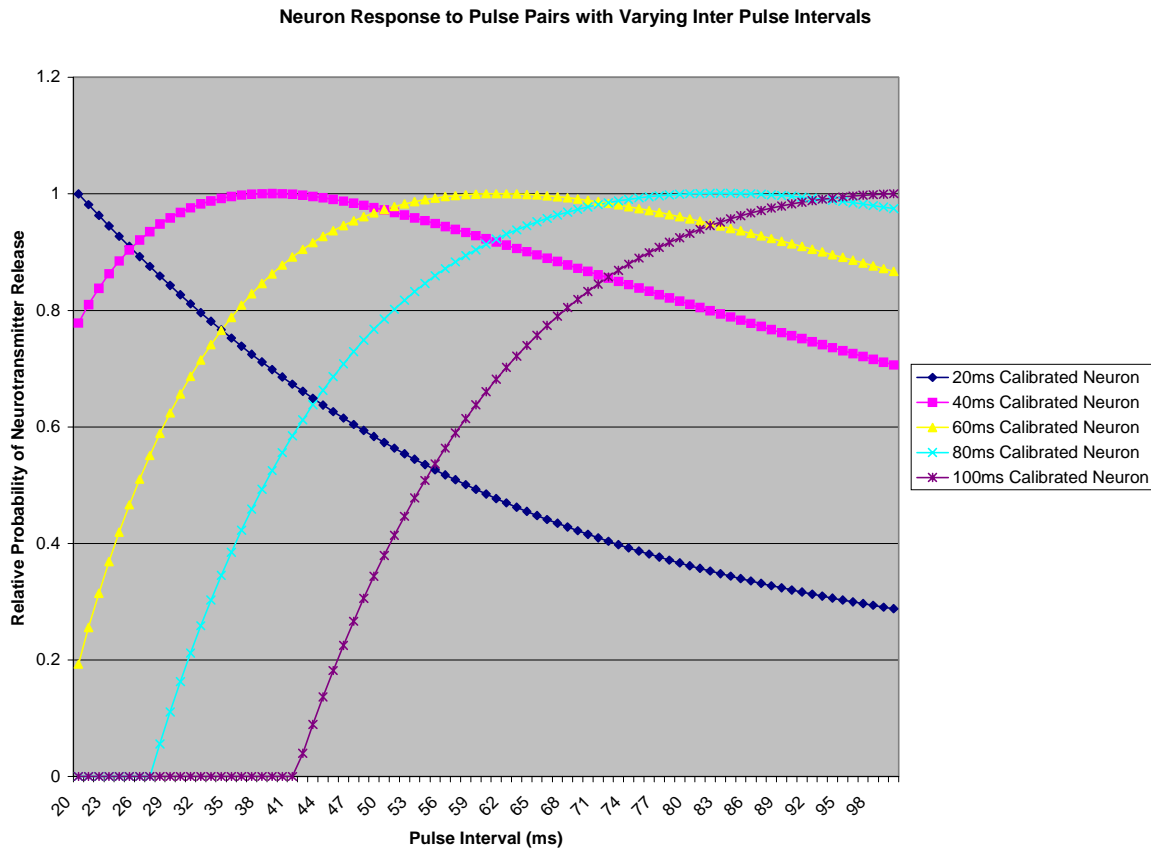
Depletion Coefficient (V) Variation



Probability of "Neurotransmitter" Release



To test the ability of the neural network to transform inter pulse intervals into a spatial pattern, and to test generalization, pulse pairs with inter pulse intervals of between 20ms and 100ms were fed into the network, and neurons' responses recorded.



**Figure 14** Graph showing that the hidden neurons respond maximally to the particular inter pulse intervals that they have been trained at, and that the network generalizes

## 7. Discussion

The graph shown in Figure 14 is very similar to one presented using a much larger network without dynamic synapses (Buonomano and Merzenich, 1995). Key differences are that neuron responsiveness in this model is not as focused around the inter pulse interval that the particular neuron has been trained at. This may be both a curse and a blessing. On one hand, it reduces the confidence level of the network. For instance, just because a 40ms neuron is firing, this is not necessarily indicative of the inter-pulse interval being exactly 40ms, because a pulse pair with an inter pulse interval of 50ms will elicit a similarly high response level. However, as will be discussed in Applications, this is not such an important task in real-world applications. In fact, it demonstrates that the generalization of the network is more robust.

In order to facilitate "neurotransmitter release" *only* for inter pulse intervals that are close to the values at which they were trained, synapse parameters or network structure could be changed. Using an alternate training method, it should be possible to adjust the parameters for  $C_0, V_0, \tau_C, \tau_V, \alpha$  so that the window at which depletion is small and facilitation is large is brief. While attempts were made to stimulate this occurrence by the brute-force training method used in this project, the most discrete neuron responses achieved are the ones shown in the graph. Instead of changing the parameters, it would also be possible to introduce inhibitory neurons. Both in biological systems and in some artificial neural networks, the release of neurotransmitters from one neuron can actually decrease the probability of release from the neuron that it is connected to. In future research, five additional inhibitory neurons will be added to the model.

The responsiveness trend of the 20ms neuron, given different inter pulse intervals, is dissimilar from the other lines plotted on the graph. It is hypothesized that this is because of a boundary condition. The brute force training method stimulated responsiveness to the desired inter pulse intervals, and reduced responsiveness to intervals higher and lower desired. Because this neuron is at the low end of the values used for training, responsiveness to values lower than it could not be reduced. However, this does not affect the network's ability to transform the tested inter pulse intervals into spatial patterns.

The brute force training method used in this model, while functional, leaves much to be desired. It is computationally inefficient, and it is not well suited to consider all the factors which should be considered in adjusting synaptic parameters. Each synapse was adjusted individually, but a more accurate implementation would manipulate the parameters of all the synapses in parallel. However, since the brute force algorithm uses nested loops to test the range of parameters, the computational expense of parallel adjustment would be prohibitive.

In an as yet unpublished paper, Zador, Maass and Natschlaeger suggest a training method suitable for networks with dynamic synapses (Zador, Maass and Natschlaeger, 1998). In order to do this, they fix the parameters  $\tau_C, \tau_V$  and  $\alpha$ , and manipulate only  $C_0$ , and  $V_0$ . Because these are coefficients and not exponents, a back propagation-like algorithm can be used. Using a training algorithm that is a derivative of back-propagation, they present a network capable of mapping one polynomial curve onto another using only twelve neurons with dynamic synapses. In the research done in this project, however, the other parameters were the ones that were adjusted most in creating the optimal parameter set. Therefore, the accuracy of manipulating only two parameters is suspect. However, in the neural network presented here,  $C_0$  was not altered at all by the brute force algorithm, although it was free to change to a wide range of values. By fixing the other parameters and manipulating only  $C_0$ , and  $V_0$  parameter sets which result in comparable performance may be possible.

Ideally, rather than training using an artificial method of altering parameters, values for  $C_0, V_0, \tau_C, \tau_V, \alpha$  would be adjusted by synaptic plasticity on multiple time scales. The current understanding is that biological systems use LTP/LTD for learning, so it should be possible to include these in the synapse model and use these to replace an imposed learning algorithm such as brute-force, or even back-propagation.

An extension of the network presented here would involve training the network on spike trains with a certain frequency instead of only pairs of pulses. Neural networks which find patterns in frequency information are particularly useful for signal processing as discussed in Applications.

While the network should perform similarly given a spike train instead of pairs of pulses, a problem arises if tetanic bursting occurs. This is when the pulse rate is sufficiently high that the neuron is put into an increasingly excited state with each pulse. This is what happens in seizures, and causes very unpredictable output.

Another possible method of improving network performance would be to use multiple synapses to connect each connected neuron pair. This would be particularly useful where a task such as the one presented here is expanded to more complex patterns. In this way, a single neuron could be monitoring, for instance, several discrete frequency bands which are each associated with noise (ie both 50Hz and 60Hz).

### **7.1. Computational Complexity**

The computational cost of a neural network is dependent on the number of neurons, the number of interconnections and the complexity of each neuron. The computational resources required for the simple integrate-and-fire type neurons presented in this system are minimal, certainly as compared with the biologically realistic networks used in (Buonomano and Merzenich, 1995). The main computational cost in the algorithm presented here is the memory and processor requirements of calculating synaptic weights while incorporating synaptic plasticity. Depending on the connectivity of the model, this may scale as anything from  $C(n) = O(n)$  (where  $n$  is the number of neurons) for a simply connected network such as the one presented here to  $C(n) = O(n!)$  for a fully connected model. Given the linear complexity of the algorithm presented here, and the small number of neurons required, the computational efficiency of this algorithm is much better than those presented in either (Wang and Alkon, 1993) or (Buonomano and Merzenich, 1995).

## **8. Applications**

Neural networks use spatial patterns for internal storage and manipulation of information. Therefore, a method which can convert temporal patterns to spatial ones can allow neural networks to perform a wide range of signal processing tasks on time series such as sound and video streams.

A function for which neural networks are particularly well suited is pattern classification. However, traditional approaches to neural network pattern classification of time series have often failed because of the network structures that have been used. Generally the values corresponding to several thousand ( $n$ ) consecutive samples are fed into the  $n$  elements in the input layer of the network. This is done for each block of  $n$  samples. The method, however, has clear limitations when patterns are more than  $n$  samples long since they overlap the neural network's window of analysis. A system which uses dynamic synapses to convert temporal input patterns into spatial representations within the neural network should rectify this problem.

Liaw and Berger, who demonstrated speaker independent speech recognition with a limited vocabulary, presented an early example of using a neural network with dynamic synapses for signal processing (Liaw and Berger, 1996). The network demonstrated an excellent capability to recognize speech under extremely noisy conditions. The next step in developing a speech recognition system on this principle would be to couple it with a more expansive processing network, which could also use dynamic synapses. A larger network would allow recognition of more patterns and thus an increased vocabulary. Also, increasing the number of synapses in the system might result in the same improvement.

Blind-signal separation, or the so-called "cocktail-party problem" involves separating the voices of individual speakers from an environment in which many people are talking. This has so far been an intractable problem for signal processing researchers. Humans are, however, particularly good at this task, and it is therefore reasonable to hypothesize that a neural network which closely models the neuronal and synaptic parameters of biological systems and can process temporal signals would be highly effective for this application.

Noise reduction is another signal processing task which is an active research topic. Using temporally sensitive neural networks to generate noise profiles, and then removing noise using either statistical methods or a neural network mapping such as that presented in (Zandor et al, 2000) could result in excellent noise reduction. A Fourier transform preprocessing step could be

used to separate the signal into frequency bands, or a layer of the network like the one presented here could perform the same task.

Another unique application for this type of neural network could be in music classification. It should be possible to construct a network in which different synapse/neuron combinations are tuned to extract patterns from various parts of the tonal range of the music. Types of music could be classified in terms of their patterns of bass notes, midrange and highs. With an automated music classifier such as this, it would be possible to extend search engine technology to search for music of various types, even without having the music manually classified. Also, it might be possible to create a fuzzy-logic search engine where if you were searching for a particular song, you would simply hum a few bars and it would cross correlate the given pattern with the database of music.

Developing neural networks with properties that closely resemble those of the human brain can lead us towards understanding brain function. Some researchers are using what they learn from neural network models with dynamic synapses to gain a certain comprehension of the auditory cortex. Not only can this help research neurologists, but also, in the long term, also people suffering from hearing loss. Novel hearing aids could be devised which transform the temporal pattern of the incoming sound into an internal spatial representation and feeds these values into the processing cortex.

## **9. Conclusion**

The objective set out for this project has been realized. A neural network has been developed which exploits the computational advantages of dynamic synapses to differentiate between pairs of pulses with different lengths of time between pulses. This temporal to spatial pattern transformation is particularly significant, because it can lay the groundwork for many neural network applications in signal processing and classification on time-series such as audio and video. Compared with previous temporal to spatial pattern transformation networks, the one presented here scales well and uses particularly few neurons and is therefore quite computationally efficient.

There remain, however, several issues which must be resolved in developing practical signal processing algorithms using neural networks with dynamic synapses. The most notable unresolved problem is the training method. Are there effective training methods for gradient-decent using dynamic synapses? Can realistic LTP-like behavior be used for training?

The ranges of inter pulse intervals which can activate neurons in the model presented are quite large. A question of import is what accuracy improvements could be made by adding inhibitory neurons to the network model?

The implications of this area of research go far beyond the comparatively simple task of inter pulse interval detection. In the long term, what can we learn about the operation of the human brain through study of realistic artificial neural networks? At the extreme of complexity and time frame, can we integrate natural and artificial neural systems for augmentation or replacement of damaged natural signal processing systems such as hearing?

The evidence presented here demonstrates the ability of small neural networks with realistic dynamic synapses to effectively convert temporal patterns into spatial ones. This is important because it goes beyond the application of pulse interval detection and opens up a powerful new paradigm for biologically realistic neural network based signal processing with countless applications.

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