`7919` `N94- 32425`

`3/135 p. 6`

# Neural Network Wavelet Technology, A Frontier of Automation

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**Abstract:**

Neural networks are interdisciplinary studies about animal brains. These have improved AI towards the 6th Gen Computers. Enormous amounts of resources were poured into this R/D awaiting for breakthroughs. International Neural Network Society held two Conferences attended by thousands each year, pushing the ultimate & exciting frontier of computing & info-tech.----our bio-brains,

Wavelet Transforms (WT) replaced Fourier Transforms (FT) favorably in every known Wideband Transient (WT) cases that began with the discovery of WT in 1985--the French geological exploration for oils by means of seismic wave imaging. The list of successful applications has the earth quake prediction, the Radar ID, speech recognitions, stock market forecasts, FBI finger print image compressions, telecommunication ISDN-data compression. More, the billion dollar medical-industrial has applications that still await the perfection--the intelligent heart beat pace-maker, the echoless hearing aids, in vivo constant level drug-dispensor, etc.

## 1. Introduction

A surging interest in neural nets began in 1980, when J. Hopfield wrote articles in Proc. Nat. Acad. Sci. p.2554 (1992) & p.3088 (1994), although pioneers such as Grossberg, Amari, Widrow, Kohonen, Fukushima, Anderson, Freeman, von der Malsburg, Rumelhart, Werbos, Carpenter, Cooper, have made significant contributions earlier. His model is simple for engineering because of interacting magnets (i.e. neuron points to the north for yes-vote, the south for no-vote) having simple matrix interconnects. Neurons are of McCulloch-Pitts (M-P) threshold logic.

## 2. Mathematical Foundation of Artificial Neural Networks

**M-P Model of the ith neuron (in alphabetic order: u-input & v-output):**

$$v_i = \sigma(u_i) = 1/(1+\exp(-u_i)); \qquad \text{Grossberg's: } (d/dt)v_i = c\,(v_i - \sigma(u_i)) \qquad (1)$$

where each voting $v_j$ is weighted by previous memory $W_{ij}$ as the net input $u_i$:

$$u_i = \Sigma_j W_{ij} v_j + \theta; \qquad \text{Hopfield's: } (d/dt)u_i = b\,(u_i - \Sigma_j W_{ij} v_j - \theta); \qquad (2)$$

$$W_{ij} = v_i v_j; \qquad \text{Hebb's: } (d/dt) W_{ij} = a\,(W_{ij} - v_i v_j) \qquad (3)$$

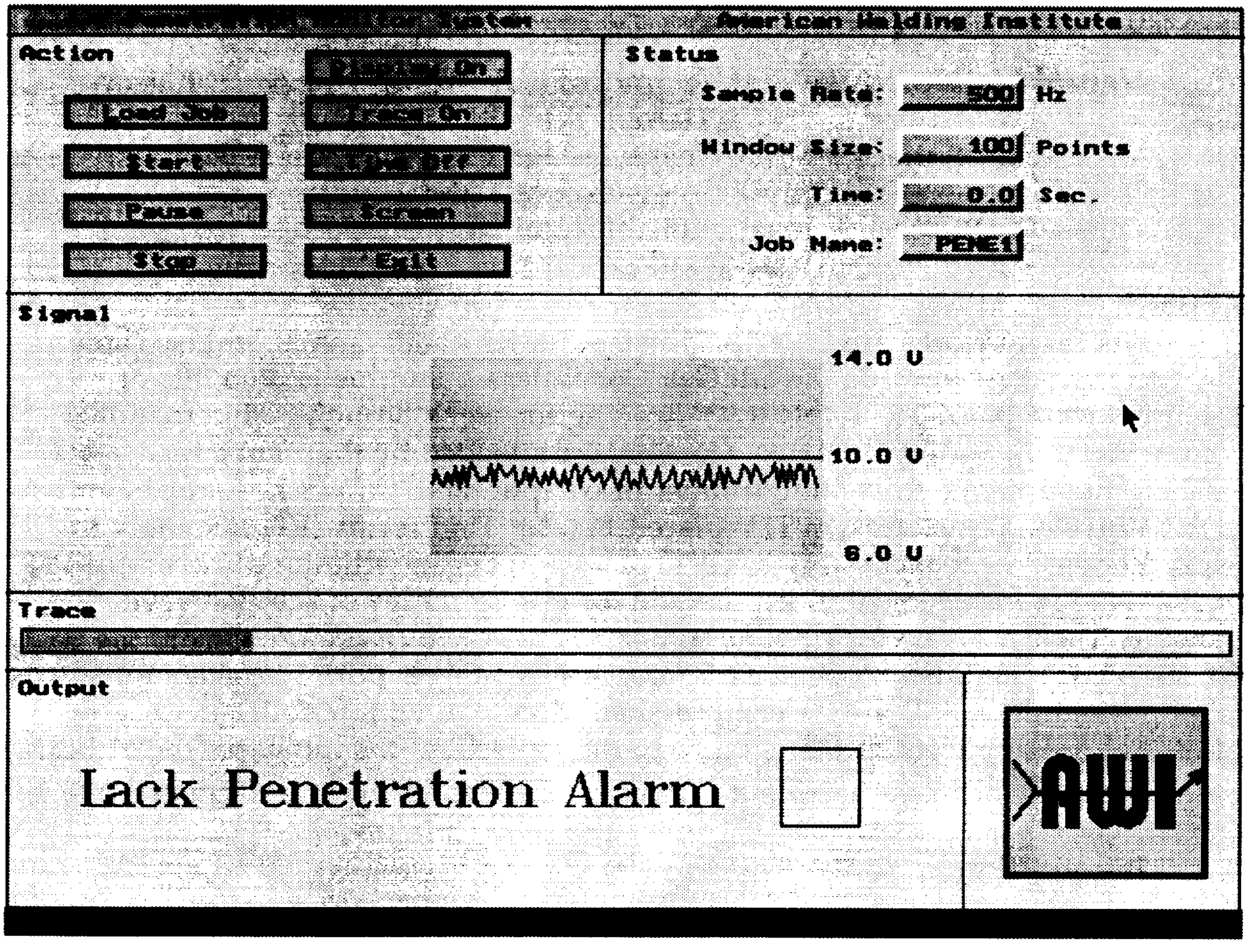


**Figure 5. The GUI of real-time welding penetration monitoring system**

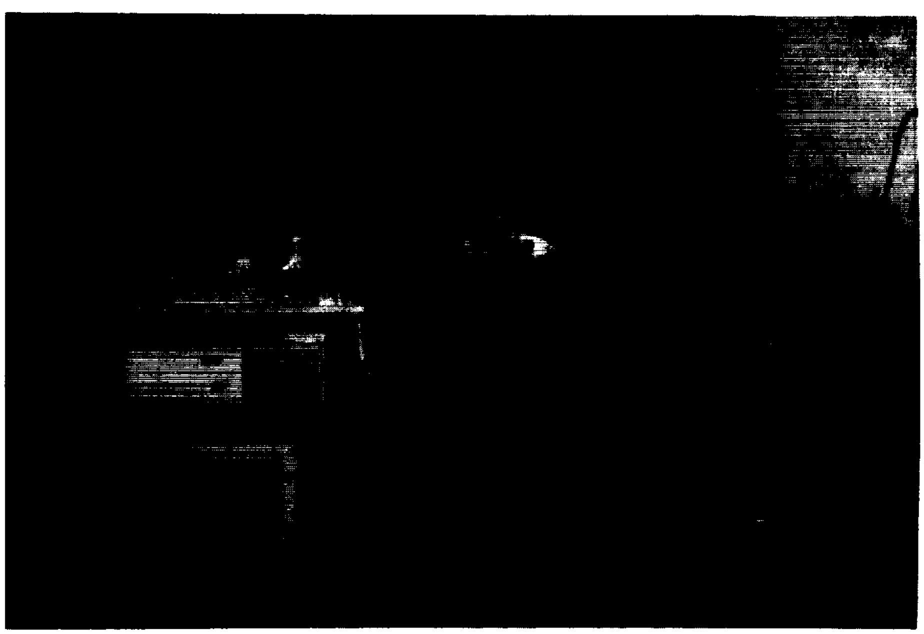

**Figure 6. The GTAW Welding Penetration Monitoring System**

All lefthand side equations are the **fixed-point solutions of righthand side dynamics.** Such a dynamic, via the synaptic vector outer products: $W_{ij}=v_i v_j$, demonstrated the Zip-Code Sorters, the Bank-Check Readers, and the OCR capabilities [1].

**Generalizations in Chaotic-Fuzzy NN chips [21]:**

Single neuron processes learnable threshold vector function $\theta_i$.

$$\theta = f(\theta); \qquad (d/dt)\theta = e(\theta - f(\theta)) \tag{4}$$

One component of $\theta$ has the change detection capability, similar to C. Mead VLSI-analog ANN book (Addison-Wesley 1989). When $\theta$ has two first order components giving one second-order equation for an oscillatory behavior similar to firing pulse trains, as shown by Szu et al. Further, if $\theta$ has a third component proportional to the need of keeping up the rapid firing, i.e. to the slope of input-output firing rates:

**Feigenbaum-Like Chaos Mapping:**

$$\theta = \alpha\,(dv/du) = 4\lambda\, v\,(1-v) \tag{5}$$

which gives, explicitly by differentiating Eq(1), the parameter $4\lambda$ giving Feigenbaum cascades toward chaos. The model Eq(4) was shown [21] to be a piecewise negative sigmoidal logic, $v_i= \sigma_N(u_i)$ with no delay, which bifurcated for fuzzy uncertainty. I believe that the "Rosetta Stone" of chaos, fuzzy logic, and neural networks has been discovered for which the fuzzy membership function is the triangle envelop of all bifurcation cascade solutions toward the chaos, that covers the full degree from imprecision to precision. The consequence in the chaotic whether prediction that dictates when the cherry in D.C. will be blooming from the imprecise spring season (but a crisp answer yes at the tip of the triangle membership function), to the bifurcation answer in the month of March or April, then further bifurcations into weeks, the days, the hours, etc. Now that a single $\sigma_N$ neuron can produce such a membership function, of which a hundred thousand of them can learn the collective experience in the chaotic associative memory. So far, we have already demonstrated the habituation and novelty detection effect form such a collection for image processing [21].

## 3. Mathematics of Wavelet Transforms, and Adaptive WT

Wavelet Transform (WT) is a linear squared-integrable transform in the inner product (Hilbert) space, just like FT. But WT must have a kernel of zero area and vanish outside a finite support. More, WT must generate all localized basis vectors by the simple affine scale-shift transformation:

$$t \quad \to \quad t' \quad = \quad (t-b)/a \tag{6}$$

where the dilation $a=2^I$ and the shift b=I, are I=± integers, rather than by Fourier global harmonics ($2\pi$ I ft). Since WT has the constant fidelity $Q = f_o/\delta f$ of which the ratio between the central frequency $f_o$ and r.m.s. width of the frequency, WT is analogous to the human inputs. Recently, adaptive WT [2] can determine its own appropriate transform kernel by the input data. A fundamental question is the completeness of the basis vectors. Thus, Adaptive WT is built by Artificial Neural Networks of which each neuron is a daughter. The set of daughter wevelet is

$$\psi_{ab}(t) \quad = \quad \psi(\,t\text{-}b/a)/\sqrt{a}, \tag{7}$$

defined by the mother wavelet $\psi(t)$ satisfying a finite power spectral density (for a derivation of admissible mother, see [3]):

$$\int df\, |\Psi(f)|^2 \,/\, |f| = c_\psi < \infty; \tag{8}$$

where $\quad \Psi(f)=\int dt\, \exp(2\pi jft)\, \psi(t)$

The integrand $|\Psi(f)|^2/|f| \neq \infty$ at $f = 0$, only if $\Psi(f=0) = 0$ gives a zero area condition: $\Psi(f=0) = \int dt\ \psi(t - b/a)=0$. The integrand is identical by changing $f \to f'=af$. All daughters have identical inner product to the mother: $(\psi_{ab}(t), \psi_{ab}(t))=(\psi(t'),\psi(t'))$.

According to the best possible classification or the most efficient representation criteria, the adaptive WT yields a composed mother from a set of admissible mothers: $\psi^{(n)}(t)$, Eq(3). Will the super-mother h(t) be admissible Eq(8)?

$$\text{Min.} \ \langle |\, s(t) - \Sigma_a \Sigma_b (s(t), h(t\text{-}b/a))\, h(t\text{-}b/a)\,|^2 \rangle \tag{9}$$

where $h(t) = \Sigma_n\, w_n\, \psi^{(n)}(t)$.

**Prove of Szu's Theorem of Adaptive Wavelet Transform with Admissible Super-Mother Condition:**

Since a square modulus is always real positive: $0 \leq |\Psi^{(m)} - \Psi^{(n)}|^2$,

then, by expanding the quadratic expression, the **Schwartz** inequality holds:

$$\psi^{(m)}\, \psi^{*(n)} + \psi^{*(m)}\, \psi^{(n)} \quad \leq \quad |\Psi^{(m)}|^2 + \quad |\Psi^{(n)}|^2$$

Use is made of Eq(4) in FT domain, we have the admissible super-mother condition:

$$\int df\, |H(f)|^2/|f| \quad = \quad \Sigma_m d_m \Sigma_n d_n \int df\, \Psi^{(m)}\Psi^{*(n)}/|f|$$

$$\leq (1/2)\Sigma_m \Sigma_n w_m w_n \{\int df\, |\Psi^{(m)}(f)|^2/|f| + \int df\, |\Psi^{(n)}(f)|^2/|f|\} \leq \infty, \quad (10)$$

which is bounded. Thus, the super-mother is likewise bounded, i.e. admissible.

**Examples:**

For the NASA mission of downward looking surveillance, such as the Earth Observation System (EOS), and DoD Mission Planning Pricision Striking Initiative, we requires a 2-D imagery sequence in time to be analyzed by 2-D wavelet adaptively. In order to illustrate the AW T, the simplest possible case is a hybrid of the human vision system response function called the Difference of Gaussian (DOG) model and the complex Gabor-Morlet wavelet in 1-D

$$h^{(n)}(t) = \exp(-t^2/a_n)\,(t^2 - b^2 n)\,\exp(2\pi j c_n t). \quad (11)$$

where $a_n, b_n, c_n$ are real constants to be determined by ANN, that could be different for different mothers.

Another interesting example is an envelope soliton for the nonlinear ocean dynamics,

$$h^{(n)}(t) \quad = \quad \mathrm{sech}^2(t-b/a)\,\exp(2\pi j c_n t) \quad (12)$$

which solves the Korteweg-DeVries equation derived from the Navier-Stokes hydrodynamics for a surface wave. Because the soliton is the exact solution of the nonlinear dynamics, this example indicates the potential that WT has---the freedom "to pay the nonlinear price first, and then enjoy the linear superposition" later. On the contrary, FT must be deferred the nonlinearity nature by first apply the linear FT to the nonlinear problem. Then, the challenge of the truncation of the NL mode-mode coupling equations remains, which may be solved only in the limit of weak nonlinearity.

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# NEW APPROACHES FOR REAL TIME DECISION SUPPORT SYSTEMS


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## ABSTRACT

NCCOSC RDT&E Division (NRaD) is conducting research into ways of improving decision support systems (DSS) that are used in tactical Navy decision making situations. The research has focused on the incorporation of findings about naturalistic decision-making processes into the design of the DSS. As part of that research, two computer tools have been developed that model the two primary naturalistic decision-making strategies used by Navy experts in tactical settings. Current work is exploring how best to incorporate the information produced by those tools into an existing simulation of current Navy decision support systems. This work has implications for any applications involving the need to make decisions under time pressure, based on incomplete or ambiguous data.


## BACKGROUND

Our research at NRaD is part of the TADMUS (TActical Decision Making Under Stress) project, funded by the Office of Naval Research. That project is generally involved with looking into new ways to enhance the decision making of Navy personnel in tactical command and control situations.

The particular focus of TADMUS is on the area of anti-air warfare (AAW), and involves situations in which shipboard commanders must make decisions about the nature and intent of aircraft that are in the vicinity of the ship. Because these situations can involve jet aircraft armed with missiles, decisions must sometimes be made in seconds even though the available information can be incomplete or ambiguous. The decisions are made by six person teams, where the ultimate responsibility for making decisions lies with the ship's commander (CO) who is closely aided by a tactical action officer (TAO).

The TADMUS research has taken two primary directions. Part of the work is involved with looking at new training approaches for the decision teams. The other primary effort involves the investigation of new approaches in the area of decision support systems. We are involved with the DSS area at NRaD.

A large part of the early DSS related work under TADMUS involved the investigation of the decision-making strategies used by experienced Navy personnel in actual tactical situations. That research took the approach of looking into naturalistic decision making. Naturalistic decision making emphasizes gathering data about how experienced decision makers make their decisions in real world settings. This approach is to be distinguished from the more artificial approaches often used in decision research, where inexperienced subjects are tested in doing unfamiliar tasks in artificial settings. One of the general ideas emerging from studies of naturalistic decision making is that it appears that experienced human decision makers are much better at making good decisions than is often suggested by more traditional research approaches.

The early TADMUS research identified two primary naturalistic decision-making strategies being used by experienced Navy personnel [5]. In most situations, those decision makers use a strategy referred to as recognition-primed decision making (RPD). This strategy relies on the use of prior experience to suggest how prototypical patterns of data may be sufficiently close to currently observed data to guide decisions about the current data [6]. When prior experience proves insufficient to guide current decisions, a second strategy comes into play using explanation-based decision making, or story generation. This strategy involves the construction of a few alternative explanations that account for the current data, followed by an evaluation of which explanation is the most plausible [8]. In both the RPD and story generation situations, selection of a course of action is expected to be automatically generated as a consequence of the situation assessment.

Two tools have been developed under TADMUS to model those strategies. An RPD template based tool takes the approach of matching current data items against a set of stored templates [7]. Those templates represent a set of typical scenarios that can be expected to occur in given tactical settings. The tool estimates the degree of fit between actual current data and the stored templates, and brings templates to the user's attention when there is a sufficiently good fit. A second tool called SABER (Situation Assessment By Explanation based Reasoning)