Optimum proximity fuzing by estimating time-dependent Doppler frequency based on wavelets and neural networks

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ABSTRACT

Proximity sensing is required for a wide range of military and commercial applications, including weapon fuzing, robotics and automotive collision avoidance. In this paper, wavelet video processing is discussed which is used for proximity sensing of nearby objects through their time dependent Doppler shift. A continuous wavelet transform is performed on the Doppler signal, after subjecting it to a time varying window, the signal features are extracted from resulting wavelet video. This is used as input to pattern recognition neural networks. The networks are trained to estimate the time varying Doppler shift from extracted features. When the Doppler shift reaches its optimum value the warhead will be initiated for optimum detonation.

Keywords: Continuous Wavelet Transform, Morlet wavelet, feed forward Neural Network, Back propagation algorithm.

1. INTRODUCTION

Proximity sensing of targets through time dependent Doppler shift can be used in Radio Proximity Fuze for maximizing the kill probability of the weapon system. There are number of techniques that can be used in Radio Proximity Fuze (RPF) to estimate optimum fuzing and detonation of warhead.

A fundamental type of information provided by the Radio Proximity Fuze is the change in frequency of the echo signal relative to emitted signal. The frequency shift is proportional to the relative velocity between the target and missile. This is well known Doppler Effect. In a simple Doppler fuzing system, as the target crosses the RPF beam, the Doppler frequency is estimated and the fuze is triggered.

The Doppler Effect arises from the relative motion between the fuze and its target. Assume the distance between the fuze and target is R, the total number of radiation wavelengths λ (corresponding to an angular phase of 2π), over the transmitted and received path, for the total phase of φ is $4\pi R/\lambda$. The rate of change in φ with time is the angular Doppler frequency ω_d which is then

$$\omega_d = 2\pi f_d = d\varphi/dt = 4\pi R/\lambda * dR/dt = 4\pi v_r/\lambda, \qquad (1)$$

Where f_d is the Doppler frequency shift and v_r is the relative velocity of the target with respect to the fuze.

The Doppler frequency shift fd then becomes

$$f_d = 2v_r/\lambda = 2v_r f_0/c \qquad (2)$$

Where f_0 is the transmitted frequency and c is the velocity of radiation propagation.

2 . METHODOLOGY

At sufficiently large distance between the fuze and target, both the relative velocity and the corresponding Doppler shift asymptotically approach a constant. As the target later passes near the fuze, the relative velocity decreases, with the frequency shift decreasing proportionately, the near the target passes the fuze, the more non-linear is the change in Doppler frequency shift over time. The general behavior is shown in Fig 1. Proximity can take advantage of this behavior in order to gain information about the target, the approach of Doppler shift to zero indicates that the target is at its closest distance from fuze. However optimum fuzing is not done at zero Doppler or closest approach of target; it depends on the warhead fragment and missile dynamics.

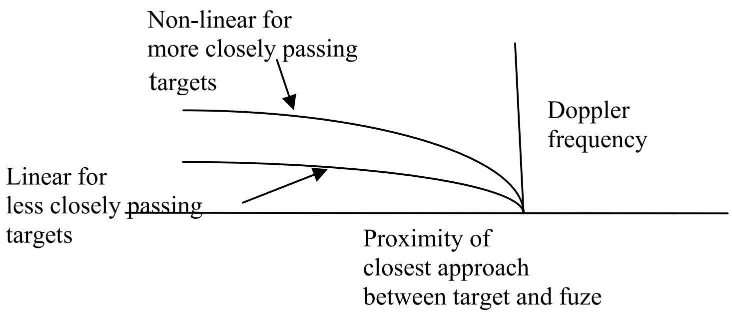


Fig 1. Change in Doppler frequency over time as target passes Proximity fuze

This paper explains the estimation of time dependent Doppler frequency based on wavelets and neural networks for proximity sensing.

In proximity fuzing with continuous wave radar, interesting signal structures are localized in time. Wavelet representations are therefore ideal, since they have both spatial and temporal localization. The radar proximity fuzing problem could then be seen as the recognition of any patterns among the time varying wavelet transform coefficients of the fuze signal that may indicate the presence of targets.

The Doppler frequency varies over time as the relative velocity between the missile and target changes. This can be analyzed through time-frequency or time-scale representation. Continuous wavelet transform is applied to the estimation of time-dependent Doppler frequency.

The continuous wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function Ψ

$$F_w(a,b) = a^{-1/2}\int_{\infty}^{\infty} f(t)\Psi\left(\frac{t-b}{a}\right)dt, a > 0 \qquad (3)$$

Where ψ(t) is real-valued Morlet wavelet

$$\Psi(t) = \cos(\omega_0 t)e^{-t^2/2} \qquad (4)$$

The continuous wavelet transform unlike the discrete wavelet transform is not restricted to dyadic time scales and therefore offers more flexibility in the analysis. The continuous wavelet transform is performed with the real-valued Morlet wavelet, which is well matched to the Doppler signals of interest. The continuous wavelet transform of Doppler signals provides information about their-time varying frequencies. This time varying information is extracted based on the scale Vs frequency relationship, i.e. frequency "f" corresponding to scale 'a' is given by

$$f= f_c*f_s/a \qquad (5)$$

Where a=scale, f_c= wavelet center frequency, f_s =sampling frequency.

The continuous wavelet transform correlates a Doppler signal with time-localized wavelets at various scales and shifts. It gives the change in local signal scale over time, which in this case is the Doppler period or inverse frequency. The samples of the wavelet transform are used as inputs to feed forward neural networks, which are trained with back propagation algorithm to estimate the time-dependent frequency of Doppler signals. For training outputs, the known instantaneous frequency of the pure signals for each time shift is being supplied.

The optimum fuzing value is then given by

$$F_{fuzing} = F_{\infty} \cos\theta_{opt} \tag{6}$$

Where θ_{opt} =Optimum fuzing angle, F_{∞}=Reference frequency

$$\theta_{opt} = \tan\text{-}1\ (V_{frag}/V_r) \tag{7}$$

$V_{frag=}$ Warhead Fragment Velocity, V_r is the relative velocity between Missile and Target.

The fuzing problem is then to estimate the Doppler frequency over time, and to fuze when the Doppler frequency reaches its optimum value.

3. DSP HARDWARE REALIZATION

Hardware is realized based on TS201 DSP processor is shown in Fig 2, first stage of this is Doppler and range extraction by correlation concept using AD8184 and NE521 respectively. AD9221 12-bit ADC is used to sample analog signals at 1.5 MHz rate.

Stage II is digital section 3 DPRAMS are used to store the 3 channels data sequentially in to processor on-chip memory, the time dependent Doppler signal is estimated and trained to get minimum error. The Hardware has been designed for a Doppler range of 5 to 150 KHz and range up to 30 meters with 3 meters resolution.

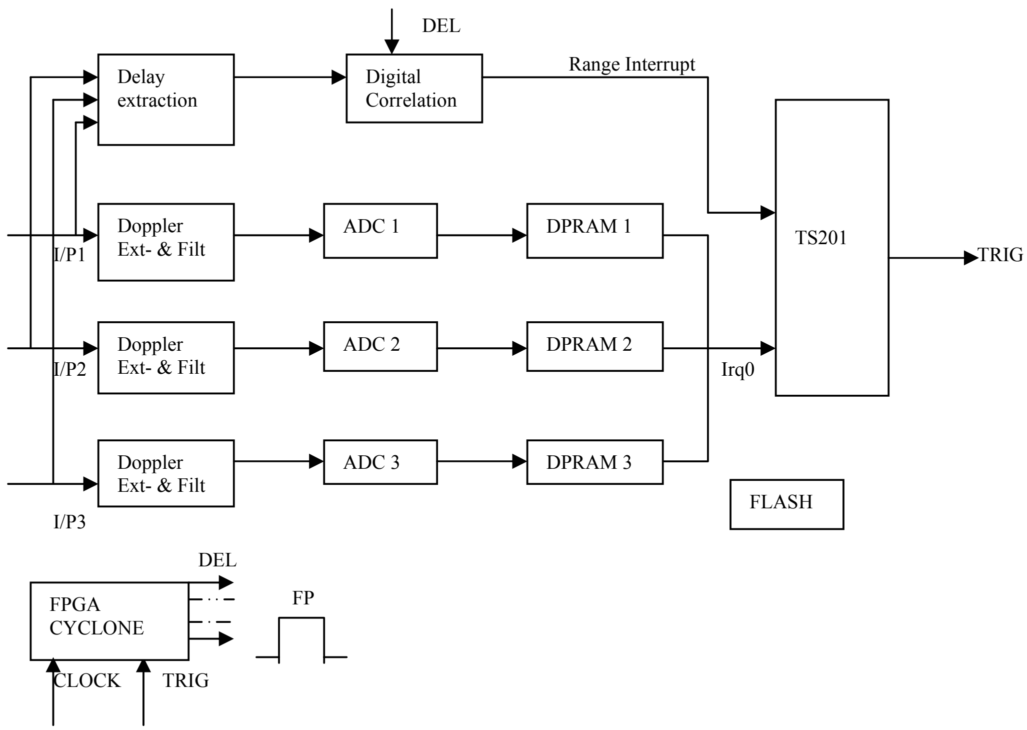


Fig 2. 3-Channel processing DSP Hardware for proximity sensing

4. SIMULATIONS AND RESULTS

Feed forward multilayer neural networks, known as multilayer perceptrons are used to extract the Doppler shift. After computing the continuous wavelet transform of the Doppler signal, sample the transform coefficients to provide inputs for the multilayer perceptrons. The networks are trained with the back-propagation algorithm to provide the Doppler shift at a given time. The most popular training algorithm is back-propagation (backward error propagation) which attempts to minimize the squared error of the network through gradient descent in weight space. Error signal for a neuron j as

$$e_j(n) = d_j(n) - y_j(n) \tag{8}$$

Where n indices the training vectors, $d_j(n)$ is the desired response for neuron j, and $y_j(n)$ is the actual response for neuron j. The instantaneous value of the sum of squared errors over all neurons in the output layer of the network can be

$$E(n) = \frac{1}{2}\sum_{j=C} e_j^2(n) \tag{9}$$

Where C includes all neurons in the output layer and N is the number of vectors in the training set. The squared error averaged over all the training vectors is given by

$$E_{av} = \frac{1}{N}\sum_{n=1}^{N} E(n) \tag{10}$$

The average squared error E_{av} constitutes a cost function that is to be minimized. It is minimized approximately by iteratively reducing E(n) for each training vector. The correction $\Delta w ji(n)$ to be applied to weight $w ji(n)$ is then defined by

$$\Delta w_{ji}(n) = -\eta \frac{\partial E(n)}{\partial w_{ji}(n)} \tag{11}$$

Where η is the parameter that determines the rate of learning. Minus sign indicates that weights are moved in opposite direction to that of error gradient

Fig 3. Shows the neural network architecture we employ for Doppler frequency estimation. The network is comprised of 3 layers of artificial neurons: an input layer, middle or hidden layer, and an output layer. Signals flow forward through the network that is from input layer to hidden layer to output layer. Simulations were carried out in Matlab, scheme was implemented in TS201 Processor assembly code, and the results were shown below.

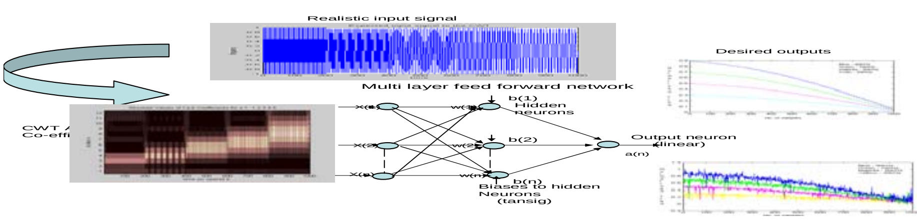


Fig 3. Feed forward neural network for training

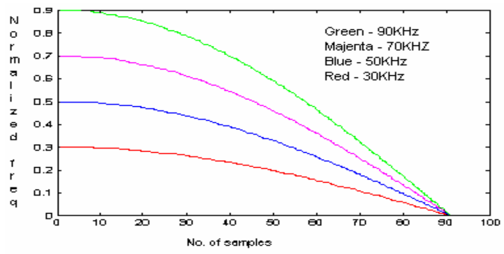


Fig 4. Desired outputs before training

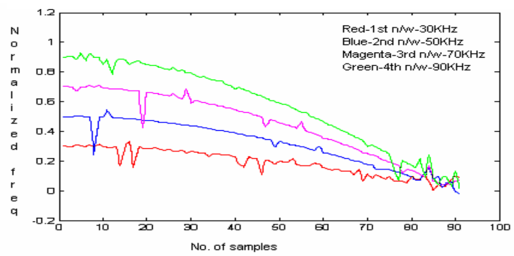


Fig 5. Actual outputs after training

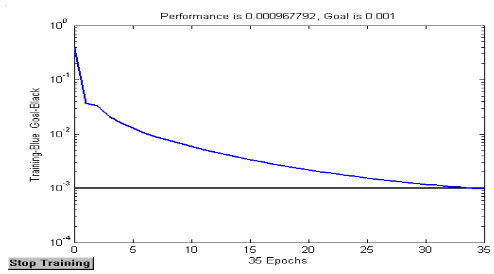


Fig 6. Network performance during training

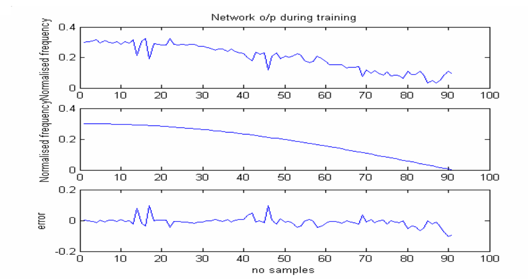


Fig 7. Network output for a 30 KHz Doppler profile

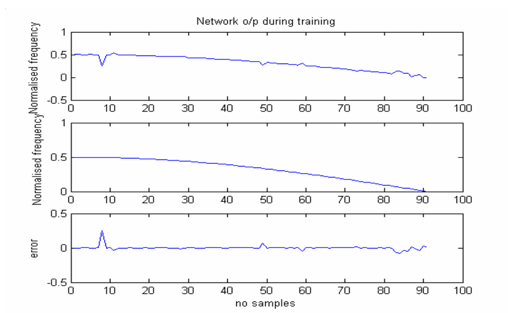


Fig 8. Network output for a 50 KHz Doppler profile

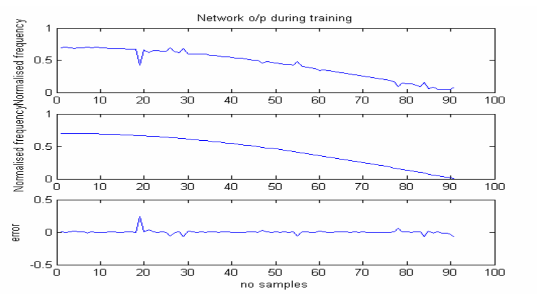


Fig 9. Network output for a 70 KHz Doppler profile

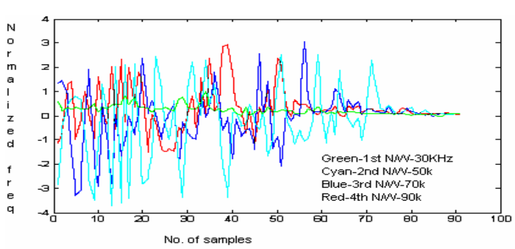


Fig 10. Error outputs of all 4 networks for 30 KHz

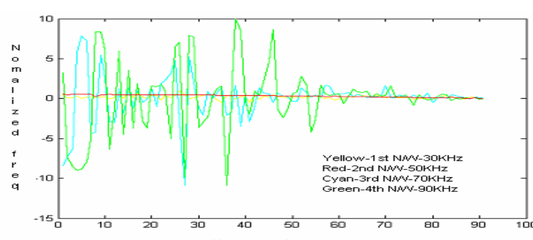
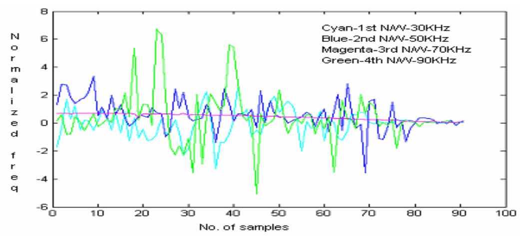


Fig 11. Error outputs of all 4 networks for 50 KHz



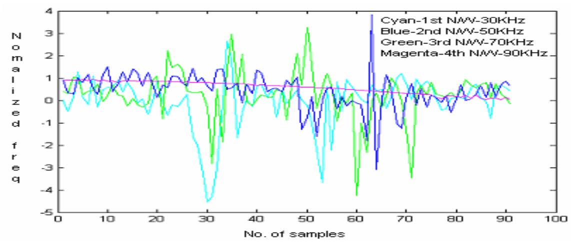
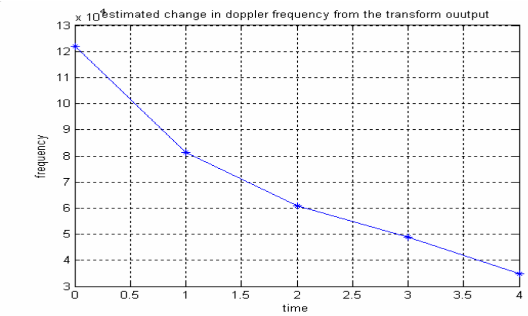


Fig 12. Error outputs of all 4 networks for 70 KHz

Fig 13. Error outputs of all 4 networks for 90 KHz



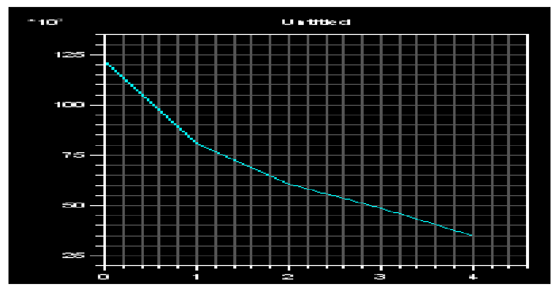


Fig 14. Doppler extraction from matlab functions

Fig 15. Doppler extraction from TS201 assembly code

5. CONCLUSIONS

Design and realization of an application specific proximity sensing has been presented, comparison of simulated and measured results shows a good agreement. This technique can be used in Surface-to-Air Missile as well as Air-to-Air Missile with high kill probability of target.

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