Estimation of Varying Doppler for Fast Moving Object Using Wavelet Generated Video

Sk Mahaboob Kamal Basha, Vijaya Bhasker Chanda, I.Hema Latha

SIR C R Reddy College Of Engineering, Eluru, Affiliated to Andhra University
RCI, DRDO, Hyderabad, India

Abstract—Estimation of fast moving object is a challenging task as far any radar system is concerned. In this paper, the wavelet video processing via the estimation of fast moving object through Doppler shift and performed the CWT(continuous wavelet transform) on the Doppler signal. Extract the signal features from the resulting video, which can be used as input to pattern recognition neural networks. The neural networks are trained to estimate the time varying Doppler shift from the extracted features. The total system consists of transmitter, receiver and DSP subsystem to process the received signal. This paper, explore the estimation of fast moving object, by using wavelet generated video using CWT and neural network technique to implement in Xilinx FPGA tools. In this paper, CWT and neural network algorithm can be implemented in MATLAB Simulink and the VHDL code is generated using Xilinx system generator software. The total system processing is executed in the FPGA board and the user only requires to apply the input data to the hardware through software. Input and output data is displayed on the computer and the results are compared using simulation software.

Keywords— Continuous wavelet transform, Doppler signal, Neural network.

1. INTRODUCTION

A fundamental type of information provided by radar is the change in frequency of the echo signal relative to the emitted signal. The frequency shift is proportional to the relative velocity between the object and radar system. This is the well-known Doppler effect. The Doppler frequency varies over time as shown in figure 1, as the relative velocity between the radar and target changes, on this Doppler signal by applying a one dimensional window at a position of Doppler signal it gives the time information at that position as the window moves on the time scale. It does not provide either time-frequency or time-scale information. It can be analyzed through time-frequency or time-scale representations, for example wavelet transform. In this paper applying the continuous wavelet transform(CWT) to the estimation of time-dependent Doppler frequency, the continuous wavelet transform, unlike the discrete wavelet transform, is not restricted to dyadic time scales, and therefore offers more flexibility in the analysis. Performing the transform is similar to a time-dependent Fourier transform with a Gabor window, except the window bandwidth changes in proportion to the centre frequency of the wavelet rather than remaining fixed.

Figure 1. Time varying Doppler signal
The continuous wavelet transform of Doppler signal provides information about their time-varying frequencies. Extract this information with feed forward multilayer neural networks, known as multilayer perceptrons. After computing the neural network processing. The networks are trained with the Levenberg-Marquardt rule to provide the Doppler frequency for a given time interval. This rule is a powerful generalization of gradient descent which employs an approximation of Newton’s method. It is much faster than standard gradient descent algorithms such as back propagation.

2. ESTIMATION OF DOPPLER SIGNAL

It is well known in optics and acoustics that if either the source or observer of an oscillating wave is in motion, the oscillation frequency appears to shift. This shift is the Doppler effect. In the case of estimation of Doppler signal the source and observer are both located in the fuze, and the Doppler effects 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 $\lambda$ over the transmitted and reflected paths is $2R/\lambda$. Since one wavelength $\lambda$ corresponds to an angular phase of $2\pi$, the total phase $\phi$ is $4\pi R/\lambda$. The rate of change in $\phi$ with time is the angular Doppler frequency $\omega_d$, which is

$$\omega_d = 2\pi f_d,$$  \hspace{1cm} (1)

where $f_d$ is the Doppler frequency shift. The Doppler frequency shift $f_d$ becomes

$$f_d \equiv \frac{2\nu}{\lambda} = \frac{2\nu c}{\lambda},$$  \hspace{1cm} (2)

and $\nu$ is the relative velocity of the target with respect to the fuze.

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

3. CONTINUOUS WAVELET TRANSFORM OF DOPPLER SIGNAL

The Fourier transform is the cornerstone of signal processing. However, it lacks time localization and less suited to the processing of Doppler signals whose frequency change over time. The time-dependent Fourier transform localizes time by performing the transform over a window, which shifts in time. However, the width of the window is fixed over the entire transform, which causes problems in the high-frequency limit. In contrast a wavelet transform has a window whose bandwidth varies in proportion to the centre frequency of the wavelet. It performs time-scale processing rather than time-frequency processing. The wavelet transform provides the local scale of the signal over time, which for Doppler signal is the local period or inverse of 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 $\Psi$:

$$C(\text{scale, position}) = \int f(t) \Psi(\text{scale, position}, t) \, dt$$  \hspace{1cm} (3)

The results of the CWT are many wavelet coefficients $C$, which are a function of scale and position.
Multiplying each coefficient by the appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal. 

\( \psi(t) \) is the real part of the Morlet wavelet, which is

\[
\psi(t) = \text{Re} \left( e^{-j n t} e^{\frac{-t^2}{2}} \right) = \cos(n \pi t) e^{\frac{-t^2}{2}}
\]

The real Morlet wavelet is a Gaussian-modulated sinusoid, well suited to processing sinusoidal Doppler signals. The wavelet transform with the real Morlet is similar to the time-dependent cosine Fourier transform with a Gabor (Gaussian-shaped) window.

Figure 2. Morlet wavelet

Figure 3 shows the Continuous Wavelet Transform of time varying Doppler signal.
4. ESTIMATION OF FAST MOVING OBJECT WITH WAVELETS AND NEURAL NETWORKS

The continuous wavelet transform correlates a Doppler signal with time-localize wavelets at various scales and shifts. It gives the change in local signal scale over time. In this case Doppler period or inverse frequency use samples of the wavelet transform as input to neural networks which are trained to estimate the Doppler signals. In this sense the wavelet transform samples can be considered signal features. Moreover, the sample continuous wavelet transform constitutes a frame rather than a basis. Such a redundant representation allows more flexibility in the selection of signal features. In terms of the most efficient signal representation, the features should be orthogonal. However, such a representation in which the features are completely independent in less robust to noise immunity and fault tolerance the search for the best representation is therefore a tradeoff between redundancy and robustness.

Figure 6. shows the neural network training architecture to employ for Doppler frequency estimation. The particular function mapping that the network performance is determined by the values of the weights between neuron layers and the internal neuron biases.
Various learning algorithms exist for computing the network weights and biases for a given problem. The most popular learning is backwards propagation, which attempts to minimize the squared error of the network through gradient descent in weight space. We can define the error signal for neuron \( j \) as

\[
\varepsilon_j(n) = t_j(n) - q_j(n). \tag{3}
\]

where \( n \) indexes the training vectors, \( t_j(n) \) is the desired response for neuron \( j \), and \( q_j(n) \) is the actual output of neuron \( j \).

We apply a powerful generalization of backwards error propagation known as the Levenberg-Marquardt weight update rule. This rule can be written in matrix notation as

\[
\Delta W = (J^T J + \mu I)^{-1} J^T e. \tag{6}
\]

where \( \Delta W \) is the matrix of weight updates, \( e \) is the error vector, and \( J \) is the Jacobian matrix of derivatives of each error to each weight. If the parameter \( \mu \) is very large, Eq. (6) approximates gradient descent, while if \( \mu \) is small it becomes the Gauss-Newton method.

The Levenberg-Marquardt update rule is known to train networks much more quickly than standard backward error propagation. It does require more memory, usually a factor of \( CN \) more. Where \( C \) is the number of output neurons and \( N \) is the number of training vectors.

Neural network gives the output graphs of training, performance & gradient as shown below.

![Network output during training](image1)

Figure 8. Network output during training

![Performance plot](image2)

Figure 9. Performance plot

Figure 8. Shows network test results, where the Doppler signal frequency decreases over time, corresponding to a relatively large closest-approach distance. The networks were tested for every time shift of the wavelet transform, network performance is relatively good.
Figure 9, shows the value of the performance function versus the iteration number. It plots training, validation and test performances.

Figure 10, shows the progress of other training variables, such as the gradient magnitude, the number of validation checks.

Figure 11, shows a regression between network outputs and network targets.

5. CONCLUSION

In this paper we have introduced a technique based on wavelets and neural networks for estimating instantaneous radar Doppler frequency. It then computes the continuous wavelet transform of the signal using the real Morlet wavelet. It provides a time-scale representation which is more appropriate for neural network processing. Samples of the wavelet transform are used as inputs to multilayer perceptron neural networks. The networks are trained to estimate the instantaneous Doppler frequency given the wavelet transform samples as input. They are trained with the Levenberg-Marquardt rule, a powerful generalization of gradient descent training. After training the networks displayed the ability to generalize, that is to estimate Doppler frequencies different than those used in training. The accurate Doppler frequency is estimated by using this process and achieved the estimation of fast moving object.
REFERENCES

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