Wavelet Technique Implementation in Forward Scattering Radar (FSR) Ground Target Signal Processing

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***Abstract*—Micro-sensor Forward Scattering Radar (FSR) is a network system used to detect and classify any ground target (personnel, vehicle) that is crossing by or entering its coverage area. The efficiency of the classification performance is highly dependent on the information extracted from the measured signal. The choice of transformation techniques that can reveal the information of the target should be chosen carefully. Hence, this reported work analyzed the implementation of Haar and Meyer Wavelet Technique (WT) that gives more detailed scales and variation information from the measured signals. The results from the wavelet technique show that we could find the similarity between signals of each target and dissimilarity between different targets.**

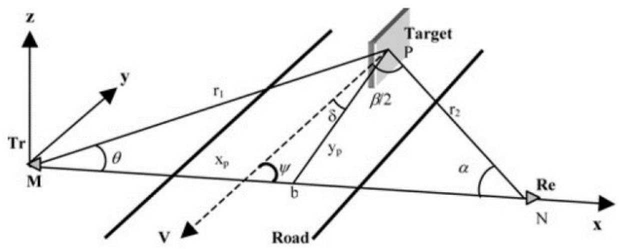
***Index Terms*—Forward Scattering Radar (FSR); Wavelet Technique (WT); Feature Extraction.**

I. INTRODUCTION

Radar network focuses on monitoring controlled coverage area for target identification and classification. Micro-sensors Forward Scattering Radar (FSR) is one of the technologies used for ground target applications. The system can identify any target, approximate any parameter and categorize any of the ground targets that automatically cross the covered area.

Target signal extraction process is to determine and identify the characteristic of the measured signals for classification purposes. However, the characteristics of the signal showed by the FSR in its time-domain signal do not provide enough target details to be used in the classification.

Hence, a different domain should be applied to examine the signal thoroughly. This task can be accomplished by applying a transformation technique, such as Laplace transform, Fourier transform and Wavelet transform. Information about the frequency can be achieved by the transformation technique using Laplace and Fourier transform. Further, more characteristics such as frequency, time and scale can be attained using wavelet transform. The transformation technique also allows the characteristics of the signals to be observed. In this case, the identification of its similarity and dissimilarity can be made as input for the classification process. However, there is a need to decide suitable transformation technique that can extract hidden information in the time-domain signals. Hence, Wavelet Technique (WT) was implemented in this work to examine the different features of the target signals collected.



$R_1 = |PM|$, $r_2 = |PN|$, $b = |MN|$, β = bistatic angle

Figure 1: FSR target detection [2]

Figure 1 shows the FSR target detection parameters. The Forward Scattering Radar (FSR) introduces a specific case of a more general class of radar, namely the bistatic radar (BR). The key peculiarity of FSR is that, in contrast to the monostatic and bistatic counterparts, they exploit an effect of electromagnetic wave shadowing a target rather than scattering from the target. This fact puts an essential restriction on the FSR topology as the target shadow exists within a relatively narrow corridor (<20^o) around the baseline, that is the line connecting the transmitter and the receiver. Another consequence is that the system loses its range resolution [1].

FSR has advantages which are: robustness to stealth targets, reasonably simple hardware, better targets cross-sections and nonexistence of signal fluctuations [11]. These advantages could be implemented into various kinds of situations; among others is the ground operation. For awareness in ground operations, micro-sensor FSR wireless network has been presented [11]. The detection, parameter estimation (for example speed) and automatic target classification (ATC) of numerous ground targets (whether personnel or vehicles) entering or crossing its coverage area are the main objectives of FSR network.

The transmitting signal bandwidth in the limiting case does not influence the range resolution and a continuous wave (CW) can be effectively used in FSR. By using lower frequency of FSR, the unknown target classification can be detected and classified. Figure 2 shows the block diagram of Automatic Target Classification (ATC) algorithm that illustrates the process on how the targets signal are measured and filtered [2].

Any signal received at the receiver is not in a suitable format to be used directly as the input to the classification process. The details of the hidden information in the measured signals must be first made visible for the ATC. Hence, transformation techniques, such as Laplace transform, Fourier transform, Z transform or Wavelet transform should be used to extract the valuable information.

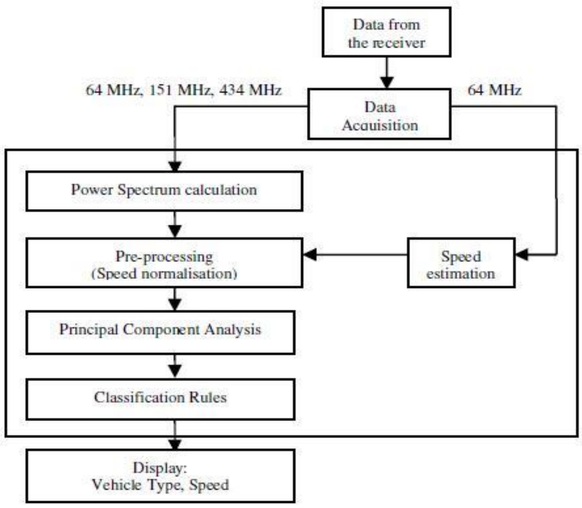


Figure 2: The ATC block diagram [1]

This work presents the use of Haar and Meyer mother wavelet in the signal transformation technique comparatively. In this paper, the Wavelet Transformation (WT) is first described. Then in Section III, the methodology of obtaining transformation WT results is presented. Section IV reports on the analysis, which is followed by the conclusion based on the results obtained.

II. WAVELET TRANSFORM

Wavelet Technique (WT) is more appropriate to be used for non-stationary signal. It has been used in many applications, such as image processing, signal processing, computer graphics, pattern recognition, data compression and the detection of aircraft and submarines and other medical image technology [3]. Wavelet technique transformation provides result in multi-resolution (MRA), which gives a better time and frequency resolution. WT wraps all the concealed characteristics of the crossing target signals. The wavelets have two types, the father wavelets and the mother wavelets, where the father wavelet integrates to one and mother wavelet integrates to zero.

$$\int \varphi(t)dt = 1 \ and \int \psi(t)dt = 0 \qquad (1)$$

The mother wavelets are useful in describing the detail and high-frequency components, while the father wavelets are good at representing the smooth and low frequency parts of a signal.

Wavelets are derived using a special two-scale dilation equation. The father wavelet and mother wavelet are defined as follows:

$$\begin{aligned} \phi(t) &= \sqrt{2}\sum \iota k\phi(2t-k) \\ \psi(t) &= \sqrt{2}\sum hk\phi(2t-k) \end{aligned} \qquad (2)$$

where *lk* and *hk* are low-pass and high-pass filter coefficients used to pass the original signal.

There are five types of orthogonal wavelet families used in practical analysis. The wavelets are the Haar, Symmlet, Coiflet, Daubechies and discrete approximation of the Meyer. Wavelets have the following important features:

- The Haar wavelet is a square wave with compact support and is symmetric, but it is not continuous unlike the other wavelets.
- The Symmlet has a compact support and is built to be as nearly symmetric as possible.
- The Coiflet is symmetric with additional properties that both φ and φ have vanishing moments.
- The Daubechies are continuous wavelet with compact support and are quite asymmetric.
- The discrete approximation of the Meyer wavelets is symmetric and continuous with compact support.

The resulting signal behavior of Haar wavelet is considered to be easy to analyze and evaluate. Comparatively, Haar and Meyer are used in this work due to their characteristics of compact support and symmetric.

Haar wavelet is normally used in decomposing signal. It is a basic and the simplest wavelet. The first Discrete Wavelet Transforms (DWT) function that has been introduced is also a Haar wavelet. Its series of rescaled “square shaped” are on -1 0 1 bit functions which altogether shaped a wavelet basis. As an orthonormal wavelet, Haar wavelet analysis is comparable to Fourier analysis, which permits a target function over an interval to be signified in terms of an orthonormal function basis. To simply group up input values, it transformation may be deliberate, passing the sum and identifying the difference. To provide the next scale, the sums are paired. This process is repeated recursively [5].

Meyer wavelet is an orthogonal wavelet. It is differentiable endlessly with infinite support and defined in frequency domain in terms of function v as in equation (3) [6]:

$$\Psi(\omega) = \begin{cases} \frac{1}{\sqrt{2\pi}}\sin\left(\frac{\pi}{2}v\left(\frac{3|\omega|}{2\pi}-1\right)\right)e^{\frac{j\omega}{2}}\ if\ \frac{2\pi}{3} < |\omega| < \frac{4\pi}{3}, \\ \frac{1}{\sqrt{2\pi}}\cos\left(\frac{\pi}{2}v\left(\frac{3|\omega|}{4\pi}-1\right)\right)e^{j\omega/2}\ if\ \frac{4\pi}{3} < |\omega| < \frac{8\pi}{3}, \\ 0 \qquad otherwise \end{cases} \qquad (3)$$

where:

$$v(x) = \begin{cases} 0 & if\ x < 0 \\ x & if\ 0 < x < 1 \\ 1 & if\ x > 1 \end{cases}$$

Clearly, one requires a different type of functions or also known as filters to pick the “main” content of a signal. Wavelet function acts like a bandpass filter that picks the changes (i.e., details) of the signal. This is where the need of scaling function, which is basically a lowpass filter. [8].

For this paper, we are using the discrete approximation of Meyer wavelet, which is FIR based approximation of the Meyer wavelet. The discrete approximation of the Meyer wavelet is symmetric and continuous with compact support [7].

III. Wavelet Processing

A. Measurement Signal

Table 1 shows the different target dimensions used for signal measurement. From the low frequency FSR network of 151MHz and the targets (car1, car2, car3 and car4), we obtained the target signals that are displayed and recorded in time domain signal. The signal did not give enough information or full details of the existing target. Initially, it was observed that the target signals have different amplitude, velocity (speed) and time.

Table 1
Vehicle Target Dimensions

Target	Target Dimensions Length	Height	Width
Car1	4.84m	1.89m	1.91m
Car2	4.26m	1.6m	1.76m
Car3	4.62m	1.43m	2.0m
Car4	4.33m	1.5m	1.84m

B. Filtering 1

Before WT method can be implemented, all of the signals were filtered and normalized using Butterworth low pass filter and Hamming window to remove noise. Normalization is required for averaging the number of signals measured for each of the targets.

C. Wavelet Transform (WT)

The essential idea of using WT is to convert the recorded target signals into a more meaningful form or function to make it more comparable. The target signals were transformed and their features were extracted via WT. Two mother wavelets, *Haar* and Meyer were implemented in CWT to extract the hidden details in the signals. Both Haar and Meyer require scaling function based on the level of iteration and central frequency. Thus, scale-time domain and coefficient were produced.

D. Power Spectrum Density (PSD)

To observe the strength of the variations (energy) as a function of frequency, power spectral density (PSD) was used. It is a representation of any particular strong frequencies variations that show at which specific frequencies variations are weak. Then, the converted signals were decomposed using DWT decomposition method and resampling the signal ratio.

E. Filtering II

The signal was calculated by passing it through a series of filters, in which subsequently the converted signal was decomposed by the DWT. The target signals, with impulse response producing in a convolution of the two, passed through a low pass filter. The decomposition of signal depends on the direction of decomposition used either in row (r) or column (c). Since this project used Haar and Meyer wavelet to normalize the ripples of the converted signal, the level of iteration has to be set. For a clearer view and indication, level 2 of iteration was set. After the decompose stage, the wavelet signal was reconstructed. The reconstruction is very essential as the decomposed signal may have lost some information during decomposition process.

F. Analysis

Based on the signal behavior, the resulted signal patterns were studied and evaluated. If the converted signal does not fulfill the performance of target signal, corrected measures will be done repeatedly on the transformation of signal and on the WT method.

IV. Results And Discussion

Figure 3 shows the time-domain signals of the four different targets measured using the FSR micro-sensor network at frequency of 151MHz. It was difficult to identify the similarity and dissimilarity of the targets from the signal analysis of the time-domain signals. Thus, clearer details can be observed by means of transformation technique.

Each target consists of a series of measured time-domain signals well kept in a database. Therefore, normalization is required to perform the averaging for all measured signals for each of the target.

Figure 4 and 5 show the filtering and normalization signals of target 2 (car2). It could be observed that by using Haar the signals normalized better as compared to using Meyer. The amplitude and shifting of each signal could be observed clearly in the results that applied Meyer in comparison to the implemented signals using Haar. Thus, result using Haar shows that the similarity of the target was superior compare to Meyer.

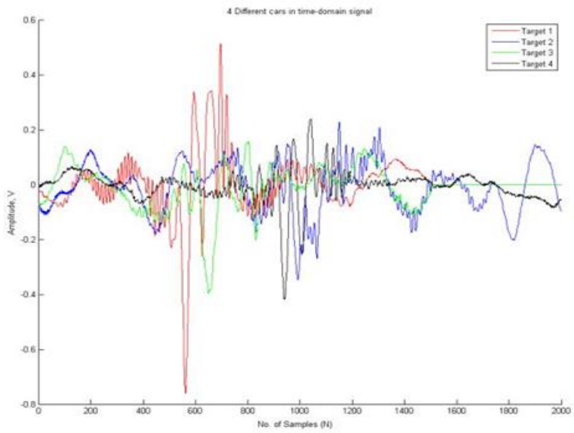


Figure 3: Targets signal in time-domain (car1, car2, car3 and car4)

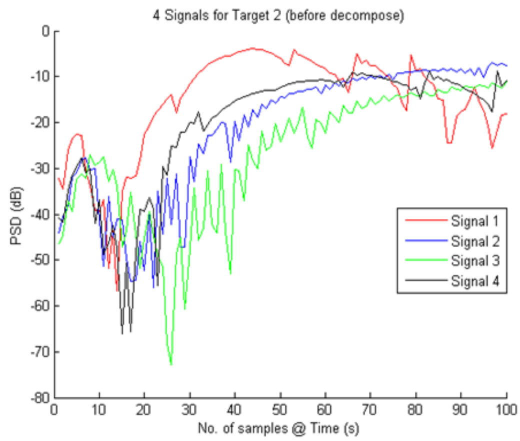


Figure 4: Four signals for car2 in PSD using Meyer (Before decompose)

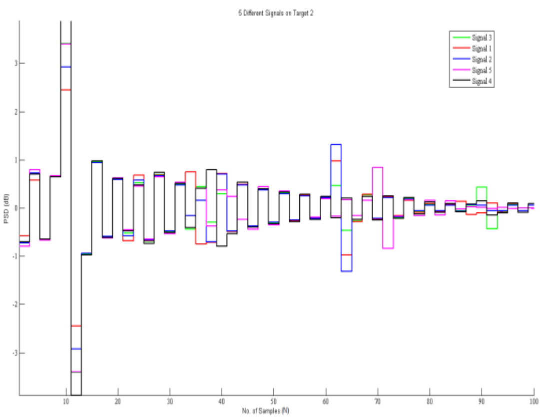


Figure 5:. Four signals for car2 in PSD using Haar (Before decompose)

Figure 6 and 7 shows PSD of all targets (car1, car2, car3 and car4) using Haar and Meyer respectively. Better signal information can be obtained from the signals when Haar wavelet was implemented as compared to Meyer. Haar showed better similarity and dissimilarity of the target signals that is the important features to be used in the classification of FSR ground targets. With reference from figures, it is proven and supported by the outcome of this work that Haar is a better choice of mother wavelet to be used for the analysis of FSR target signals.

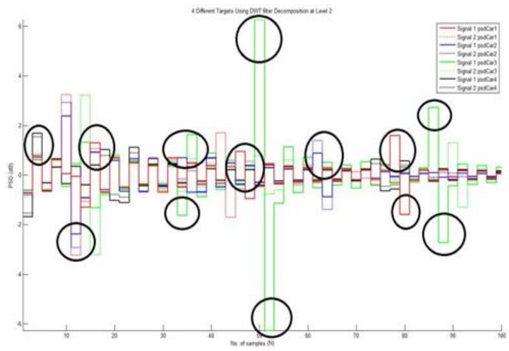


Figure 6:. All target signals in PSD by Haar

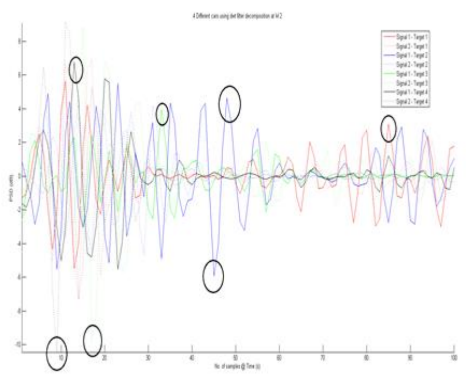


Figure 7: All target signals in PSD by Meyer

V. Conclusion

The details among the targets were extracted using Wavelet Technique (WT) of Haar and Meyer to extract different signatures of target signals. Results were represented by Power Spectrum Density (PSD) and based on the shifting and amplitude of the processed signals. Haar displayed square shape representation and Meyer displayed cone shape representation. Both WT results suggest that the signatures of the target signals depend on the level of PSD that is related to the velocity and shape of the target. Haar wavelet technique is proven to be more suitable for the extraction of hidden information as compared to Meyer since similarity and dissimilarity of the targets can be observed clearly form the plotted and decomposed signals.

Acknowledgement

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References

[1] Rashid N. E. A., M. A., Jancovic P., Sizov V., Abdullah R., Cherniakov M. 2011. Automatic Target Classification in a Low Frequency FSR Network. *IEEE.*

[2] Sifuzzaman M., Islam M. R., and Ali M. Z. 2009. Application of Wavelet Transform and its Advantages Compared to Fourier Transform. *Journal of Physical Sciences*. 13: 121-134.

[3] Yunhui, S. and Qiuqi R. 2005. Continuous wavelet transforms. in Signal Processing, 2004. Proceedings. ICSP'04. *2004 7th International Conference. IEEE.*

[4] Heil, C.E. and Walnut D.F. 1989. Continuous and discrete wavelet transforms. *SIAM review*. 31(4): 628-666.

[5] Meyer Y. 1990. Ondelettes et Operateurs, *Hermann*.

[6] Dghais A. A. A. and Ismail M. T. 2013. A Comparative Study between Discrete Wavelet Transform and Maximal Overlap Discrete Wavelet Transform for Testing Stationary. *International Science Index*. 7(12).

[7] Donoho D., Kerkyacharian G., and Picard D. 1995. Wavelet shrinkage: Asymptopia? *J. Roy. Sat. Soc*., 1995. 57: 301-369.

[8] Lepik, Ü. 2007. Application of the Haar wavelet transform to solving integral and differential equations. in *Proceedings of the Estonian Academy of Sciences, Physics, Mathematics*.

[9] Ngui, W.K., et al. 2013. Wavelet Analysis: Mother Wavelet Selection Methods. *Applied Mechanics and Materials*, 2013. 393: 953-958.

[10] Wavelet Families. 2014. Retrieved from http://www.mathworks.com/help/wavelet/ug/wavelet-families-additional-discussion.html

[11] Skolnik, M.I., An Analysis of Bistatic Radar. *Aerospace and Navigational Electronics, IRE Transactions on*, 1961. ANE-8(1): 19-27.