Basha et al. 2024. *Int. J. Vehicle Structures & Systems*, 16(2), 198-203
ISSN: 0975-3060 (Print), 0975-3540 (Online)
doi: 10.4273/ijvss.16.2.11

International Journal of
Vehicle Structures & Systems
Available online at https://yanthrika.com/eja

Detection and Estimation of Coordinates of Small Sized Ground Objects MIMO Radar with Wavelet Signal Processing

Syed Asif Basha[a,g], S. Sujatha[b], P. Subhashini[c], R. Jothi Chitra[d], S. Navaneethakrishnan[e] and C. Rajanandhini[f]
[a]*Dept. Computer Engg., College of Computer Science, King Khalid University, Abha, Kingdom of Saudi Arabia*
[g]*Corresponding Author, Email: sbashaa@kku.edu.sa*
[b]*Dept. Electrical & Electronics Engg., Srisairam College of Engg., Anekal, Bangalore, India*
[c]*Dept. Information Tech., Vel Tech Multi Tech Dr. Rangarajan Dr. Sakunthala Engg. College, Chennai, Tamil Nadu, India*
[d]*Dept. Electronics & Comm. Engg., Velammal Institute of Tech., Chennai, Tamil Nadu, India*
[e]*Dept. Mech. Engg., Erode Sengunthar Engineering College, Perundhurai, Tamil Nadu, India*
[f]*Dept. Electronics & Comm. Engg., Periyar Maniammai Institute of Sci. & Tech., Thanjavur, Tamil Nadu, India*

ABSTRACT:

A study was carried out on algorithms for detecting small-sized ground objects (LSGs) using Haar and Daubechies wavelet filtering. The dependences of the probability of correct detection on the signal-to-noise ratio in the MIMO 2x2 and MIMO 4x4 channels were obtained using Haar and Daubechies wavelet filters at different UAV speeds. A study of algorithms for estimating errors in the angular position of the INR using Haar and Daubechies wavelet filters was carried out. The dependences of estimates of errors of the angular position of the INO on the signal-to-noise ratio at UAV speeds of 20, 40 and 100 m/s for MIMO 2x2 and MIMO 4x4 were obtained.

KEYWORDS:

Haar; Daubechies; Wavelet filtering; MIMO radar

CITATION:

S.A. Basha, S. Sujatha, P. Subhashini, R.J. Chitra, S. Navaneethakrishnan, and C. Rajanandhini. 2024. Detection and Estimation of Coordinates of Small Sized Ground Objects MIMO Radar with Wavelet Signal Processing, *Int. J. Vehicle Structures & Systems*, 16(2), 198-203. doi:10.4273/ijvss.16.2.11.

1. Introduction

Detecting and estimating the coordinates of small-sized ground objects using Multiple Input Multiple Output (MIMO) radar with wavelet signal processing can be a challenging but effective approach. MIMO radar systems utilize multiple antennas for both transmitting and receiving, enabling better spatial resolution and improved target detection and localization [1-2]. Wavelet signal processing can enhance the ability to detect and estimate the coordinates of small objects by providing a multi-resolution analysis of the received signals. Here's a step-by-step guide on how to approach this problem: System setup starts with antenna configuration which design and set up the MIMO radar system with multiple antennas for transmitting and receiving. The number of antennas will affect the system's spatial resolution. Then comes frequency and waveform design to choose appropriate radar frequencies and waveforms that are suitable for detecting small objects. Shorter wavelengths are better for resolving small targets. Next data collection includes transmit and receive signals which transmit radar signals and receive the reflected signals from the objects of interest. This collects data over multiple antenna elements to capture spatial information [3].

Preprocessing includes noise reduction which applies noise reduction techniques to the received signals, such as clutter removal and interference cancellation. Next wavelet transform is used to analyze the radar data in both time and frequency domains. The wavelet transform can provide multi-resolution analysis, which is crucial for detecting small objects with varying scales. Haar or Daubechies wavelet is chosen as the basis for the wavelet transform. Haar wavelets are simple and suitable for basic feature extraction, while Daubechies wavelets offer better frequency localization and are more versatile [4-5]. Li et al [6] provided a comprehensive introduction to MIMO radar systems, including waveforms, beamforming, target detection, and parameter estimation. It offers valuable insights into the theoretical foundations of MIMO radar and its signal processing techniques. Zhu et al [7] covered various applications of wavelets, including radar signal processing. It provides a good foundation for understanding the use of wavelets in signal denoising, feature extraction, and target detection.

Shi et al [8] discussed the use of MIMO radar systems for target localization and image reconstruction. It explores the benefits of MIMO radar in terms of spatial resolution and improved detection performance. Lv et al [9] presented a study on the use of wavelet transform techniques for Ground Penetrating Radar (GPR) imaging. Although focused on GPR, the wavelet-based approach can be relevant for small-sized ground object detection in other radar systems as well. Tong et al [10] explored MIMO radar imaging techniques for detecting and localizing aerial targets. It discusses sparsity-based models and wavelet-based processing methods to improve target detection and localization accuracy. Hoffmann et al [11] focused on the application of wavelet-based processing in MIMO radar systems for detecting and tracking low-flying air targets. An et al [12] explored the use of wavelet transform in Inverse Synthetic Aperture Radar (ISAR) imaging, which is relevant for target recognition and localization. It demonstrates the effectiveness of wavelet-based techniques for small target imaging. Ding at al [13] discussed the use of MIMO radar with waveform diversity and wavelet-based sparse recovery techniques for target detection and localization. It emphasizes the role of sparsity in improving radar performance.

2. MIMO systems

During recent years, wireless systems that make use of multiple antennas in the transmitter and receiver, systems known as MIMO, have seen their use and popularity increase very rapidly [2]. One of the main handicaps one faces in wireless communications is multipath fading. Multipath propagation refers to the arrival of the transmitted signal to the receiver through different paths. In these trajectories the signal experiences time delays, different angle of arrival and frequency variation (i.e. Doppler effect) due to the dispersion of electromagnetic waves. In this way, the received signal varies in power, time, frequency, and/or all of them at the same time through the superposition of all the multipath elements that affect the receiver. This random fluctuation of the signal that produces this phenomenon is known as fading and can seriously affect our communications system. In addition to this phenomenon, the restrictions derived from power limitations and bandwidth scarcity make MIMO one of the most reliable techniques to achieve the high transmission rates required by the current communications. While SISO (single-input single-output), its predecessor, takes advantage of time and frequency to obtain greater performance in its communications, MIMO allows exploiting the spatial dimension provided by the use of multiple elements in the transmitter and the receiver.

Unlike a system with only one antenna, MIMO systems allow transmitting through several elements at the same time and receiving in the same way at the receiver. This data redundancy in the transmitter and receiver translates into a substantial improvement in the capacity of communications systems and protection against dispersive phenomena frequently present in telecommunications. We can see in a simple example the effect in terms of gain that comes with making use of the spatial dimension that MIMO allows us to benefit from. Assuming a constant channel response throughout the bandwidth of interest and specifying in terms of transmission rate, if we have a SISO system, if the number of total antennas in transmission and in reception it is MT = MR = 1, it is possible to reach transmission rates of 1 Mbps. If instead of using a single antenna at both ends, we use MIMO systems of MT = MR = 2 under the same conditions, we can achieve rates of 2 Mbps. In the same way, if we increase up to MT = MR = 4 the transmission rate achieved increases up to 4 Mbps. The SISO system would also be capable of reaching transmission rates of 4 Mbps increasing its bandwidth in the same proportion or raising the transmission power by 60 dB, something completely unfeasible. The choice between MIMO 2x2 and 4x4 configurations depends on the specific requirements of the communication system and the trade-offs between capacity, complexity and performance.

3. Wavelet transformation

Wavelet transformation is a way to distinguish the individual components of any signal (e.g. sound, music, sensor signal) from which the signal is composed and display them appropriately. It thus performs something similar to the Fourier transform (FT) and its derived versions (DFT, FFT, STFT), but achieves far more accurate results for some signals. The wavelet transformation is therefore a computational algorithm suitable for implementation on a DSP (signal processor) or a PC, based on comparing the analyzed signal with a pre-selected short waveform, the so-called wavelet. And it is the value/level of similarity for different displacements and expansions of the wavelet with respect to the signal that is the desired result of the transformation. Wavelet transformation can be used to filter out unwanted interference or as lossy compression. After splitting the signal into components, it is possible to remove/delete the components with little effect and reassemble them to obtain a digital signal with a smaller amount of data, i.e. file size.

The whole principle of the basic computational algorithm of the wavelet transformation CWT (Continuous Wavelet Transformation) consists in mutual comparison of the analogue signal $x(t)$ with the selected sample shape, referred to as the wavelet ψ (wavelet). From a distance, it is something similar to comparing differently shaped objects to some basic geometric shape such as a cube, cuboid, cylinder, cone or sphere. The result of the comparison is the coefficient-value of $CWT(\tau, s)$ indicating the level of similarity of the pattern-wave with the signal. Since the analysed signal is very long compared to the sample wavelet, the comparison itself is performed by the method of gradually moving the wavelet with respect to the signal by a constant step = time shift τ. The result is a sequence-a series of numbers indicating the similarity of the wavelet to the signal at a specific moment in time (Fig. 1).

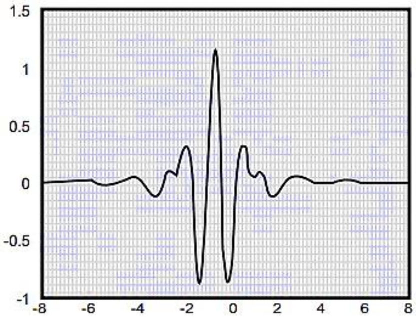

Fig. 1: Meyer wavelet - waveform amplitude course (vertical axis) in time t (horizontal axis)

Another thing is that a certain piece of signal can be similar in shape to a wavelet, only it is time-stretched or shrunk against it. For example, a wavelet has a length of 40 ms, and a piece of a similar waveform is only 20 ms. Therefore, in addition to the time shift of the wavelet, it is also gradually "stretched" to different lengths, the so-called change of scale with CWT can be expressed mathematically by the following relation:

$$CWT(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t)\, \varphi * \left(\frac{t-\tau}{s}\right) dt$$

The analysed signal *x(t)* is taken and the selected waveform $\boldsymbol{\psi}$ of a certain scale $\boldsymbol{s}$ is taken from the "table menu". By successively shifting the wavelet against the signal, its similarity is determined in X specific moments of time according to the formula. It then rescales the wavelet and compares it again to the signal at the same time instants. And this is "done" all the time, for Y scales of the wavelet. The result is thus a matrix of similarity values for X time displacement and Y scales of the wavelet. This is similar to the STFT (Short-Time Fourier Transformation) spectrogram, where the result is a matrix of signal amplitude values for X time displacement and Y values of the frequencies. By comparing the two matrices, the dependence between the scale of the wavelets can be found and frequency *f*, *s=1/f*. That is that the small scales of the wavelet correspond to the detection of high frequency signals. The big difference is in the resulting "structure" of the matrix (Fig. 2).

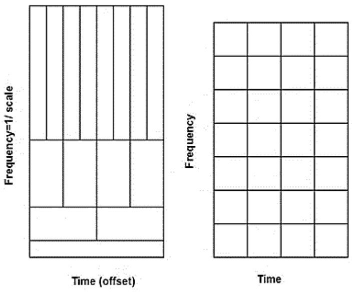

Fig. 2: Wavelet transform spectrogram (left) and STFT (right)

While in the case of the STFT spectrogram it is divided into regular, equal-sized areas that do not respect the shortening of the time period of the signal for high frequencies, the "structure" of the matrix of the discrete wavelet transform DWT respects the shortening of the time period of the high-frequency components of the analysed signal. That is that the wavelet transform algorithm involves a variable window length, while in STFT the window length is still fixed. However, since the content of the marked rectangles DWT is the same as the content of the STFT squares, i.e. express the same signal energy, the results achieved are equivalent. The most commonly used wavelets are shown in Fig. 3.

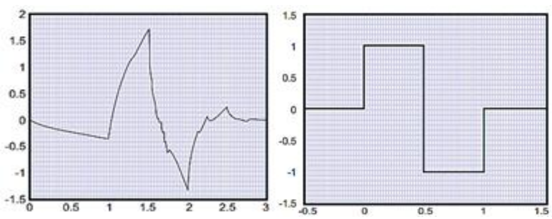

Fig. 3: Daubechies 2 wavelet (left) and Haar wavelet (right)

4. Simulink MatLab models of a chirp and PCM radar signal generator

Below are the steps to create Simulink models for both types of signals. A chirp signal is a signal whose frequency increases or decreases with time. In order to create a chirp signal generator in Simulink use the "Sine Wave" block as the signal source. It is configured to generate a sine wave with a frequency that changes linearly with time to create a chirp signal. Then a time-varying frequency input is used, either by specifying a time-varying frequency as an input or by using a ramp or other function generator block. Then a block is used to control the amplitude of the chirp signal. PCM is a method of digitally representing an analogue signal. In order to create PCM radar signal generator in Simulink involves analogue signal source that represents the radar signal to digitize. "Sample and Hold" block is used to simulate the sampling process. This block will sample the continuous analogue signal at discrete intervals. Quantization is implemented by rounding the sampled values to a specific number of bits using a "Quantizer" block. This block will quantize the continuous signal into discrete levels. The quantized signal is encoded into a PCM code.

5. Results and discussion

The wavelet transform is similar to the windowed Fourier transform, but with a different evaluation function [1, 2]. The Haar wavelet is shown in Fig. 4. The paper presents Simulink MatLab models of a chirp and PCM radar (RL) signal generator. In chirp Simulink model, the signal will have a frequency that linearly increases or decreases over time, which is characteristic of a chirp signal. One can analyze the signal's properties, such as its frequency sweep rate, duration, and amplitude, by inspecting the scope's output. Depending on the parameters, one can observe how changes in the input parameters affect the chirp signal. In PCM radar Simulink model, the signal will consist of discrete amplitude levels, representing the quantized values. One can analyze the bit depth (number of quantization levels) and the encoding scheme to understand how the analog signal is digitized. The scope output will show the PCM code's binary representation, allowing you to inspect the digital signal's characteristics. Ultimately, these Simulink models serve as valuable tools for signal generation and can aid in understanding the behaviour and characteristics of chirp and PCM radar signals, which are essential in radar system design and analysis.

A Simulink MatLab model of a radar channel with additive noise and Doppler shift (for different carrier speeds) has been developed for transmitting/receiving chirp and PCM signals, as well as a target simulator, which allows estimating the range to the target depending on the Enhanced Permeability and Retention (EPR). As a result of the simulation, signals at the output of the radar channel with noise, a filtered signal and additive noise in the radar channel for the Haar and Daubechies wavelet filters were obtained. A software package has been developed that includes a radar signal shaper, a radar channel model with additive noise and a Doppler channel, Haar and Daubechies wavelet filters and a target simulation unit for assessing the effectiveness of target detection (Fig. 5).

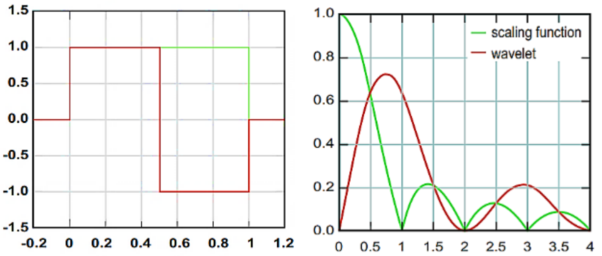

Fig. 4. Haar scaling function and wavelet (left) and their frequency components (right)

MIMO 4x4 and MIMO 2x2 channels are modelled by considering path loss, shadowing, multipath fading, and the impact of UAV motion on the channel. Radar signals are generated for different UAV speeds (20 m/s, 40 m/s, and 100 m/s) which account for Doppler shifts caused by UAV motion. Noise is added to the received signals to simulate different SNR scenarios. The noise should be representative of real-world radar system noise. The radar targets or objects are modelled that the radar system is detecting by considering their radar cross-sections (RCS), locations, and motion. A detection algorithm is implemented, such as Constant False Alarm Rate (CFAR) or matched filtering, to detect targets in the received radar signals. Monte Carlo simulations are conducted to run multiple trials for each combination of channel, SNR, filtering, and UAV speed. This accounts for statistical variations in detection performance. Dependence of the probability of correct detection (with a false alarm probability of 0.0001 and ESR 1 m2) on the signal-to-noise ratio in the MIMO 4x4 (left) and MIMO 2X2 (right) channel (green - without filtration, blue - Haar filter, red - Daubechies filter) is shown in Fig. 6.

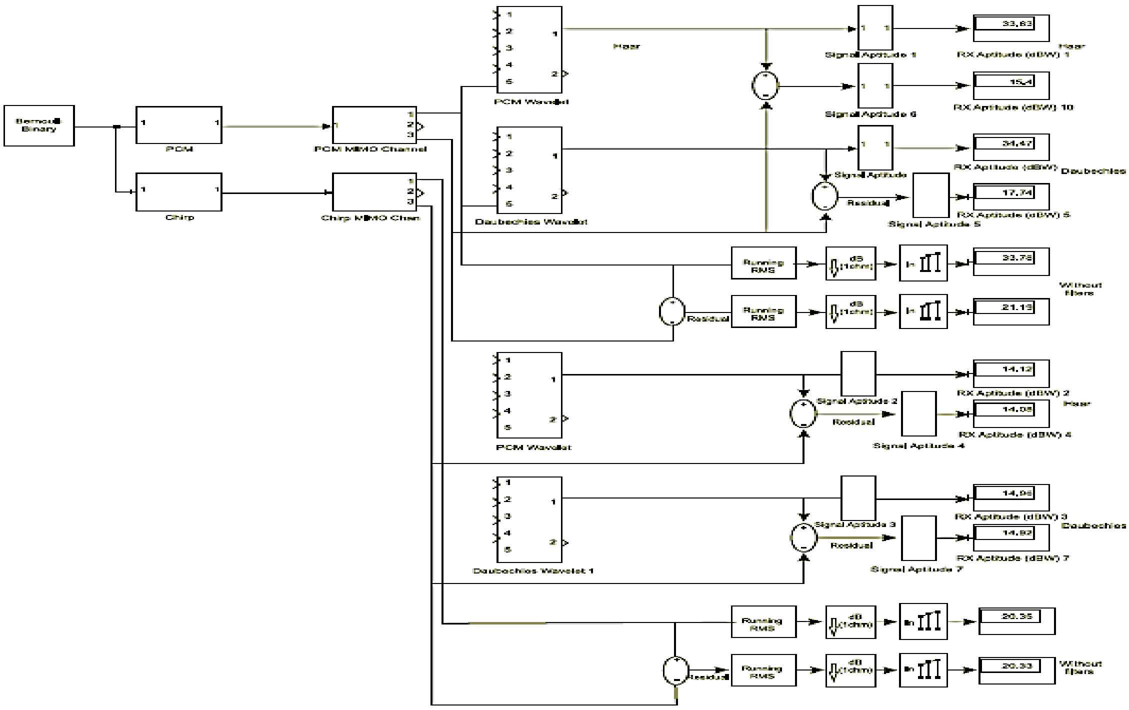

Fig. 5. Software package for evaluating the effectiveness of target detection

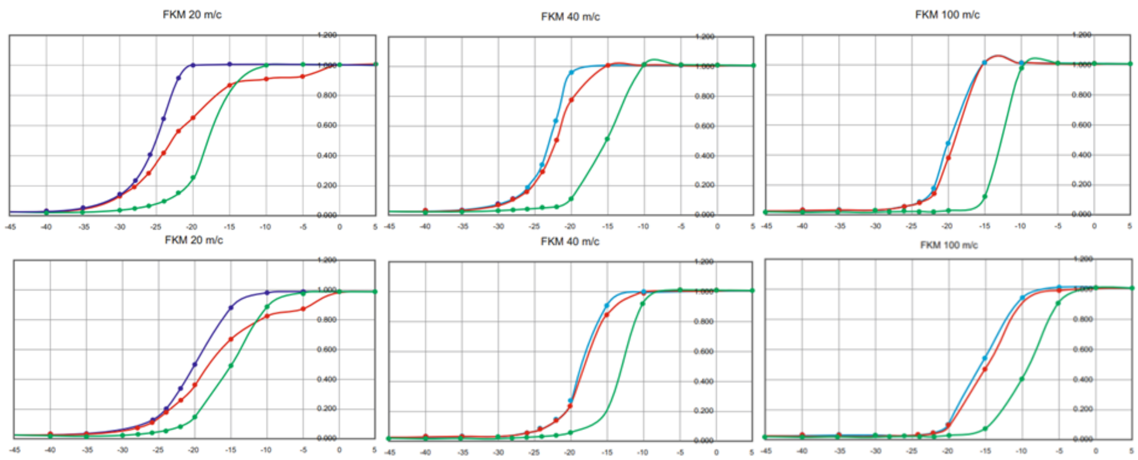

Fig. 6: Dependence of the probability of correct detection on the signal-to-noise ratio in the channel - MIMO 4x4 (top) and MIMO 2x2 (bottom) (green - without filtering, blue - Haar filter, red - Daubechies filter) for UAV speeds of 20, 40 and 100 m/s (left to right)

From the graphs of the probability of correct detection as a function of the signal-to-noise ratio (Fig. 6), the efficiency of wavelet filtering increases for the MIMO 4x4 radar channel compared to the MIMO 2x2 radar channel. The excess probability of correctly detecting a unit is explained by "filtering" when constructing graphs in Excel software. To study the influence of wavelet filtering on the estimation of signal parameters, a Simulink MatLab model was developed, into which channels for estimating the "error" of the angular position of the target were added [4] (Figs. 7 & 8). The software package includes a radar signal generator, a MIMO model of a radar channel with additive noise, a Doppler channel, Haar and Daubechies wavelet filters, and channels for estimating the "error" of the angular position of the target. MIMO 4x4 and MIMO 2x2 channels are modelled by considering path loss, shadowing, and multipath fading effects, which can be modeled using mathematical channel models like Rayleigh or Rician fading. The radar signals are generated for different UAV speeds (20 m/s, 40 m/s, and 100 m/s). This includes generating the transmitted radar waveform and accounting for Doppler shifts due to UAV motion. Then noise is added to the received signals to simulate the effects of SNR.

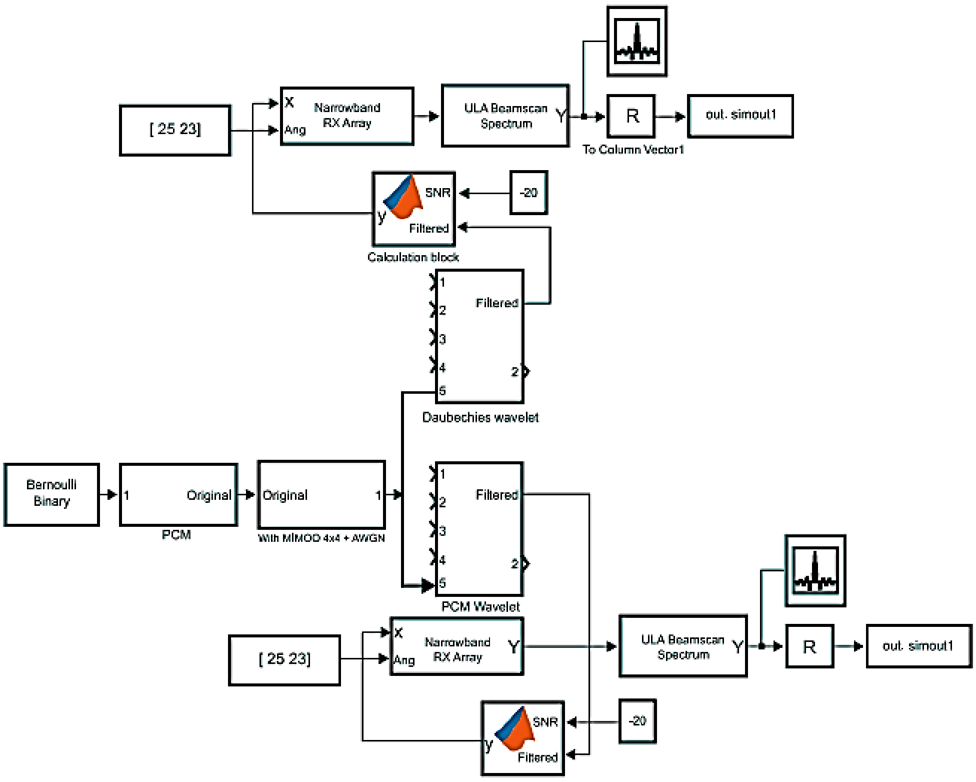

Fig. 7. Software package for studying the influence of wavelet filtering of signals on the error in determining the angular position of a target

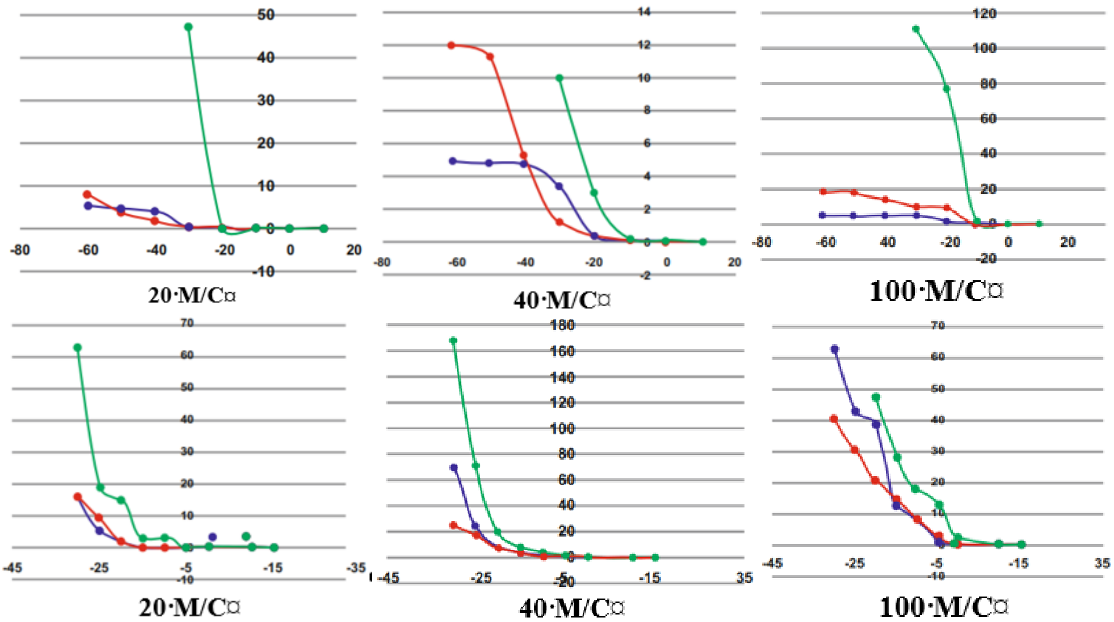

Fig. 8: Dependence of estimates of "errors" of angular deviation on the signal-to-noise ratio in the MIMO 4x4 (top) and 2x2 (bottom) channels (green - without filtering, blue - Haar filter, red - Daubechies filter) for UAV speeds of 20, 40 and 100 m/s

The noise should be representative of the real-world noise in the radar system. Filtering is performed with Haar and Daubechies to denoise and enhance the radar signals. Algorithms are implemented for angular deviation estimation. This step typically involves processing the received signals to estimate the direction of arrival (DOA) or angular deviation of the detected objects. It is possible to increase the accuracy of measuring signal parameters when using wavelet transforms, as well as when using Haar and Daubechies wavelets by two or more times. The dependences of estimates of “errors” of angular deviation on the signal-to-noise ratio in the channel are presented in Fig. 8. A study of signal processing algorithms when estimating their parameters using Haar and Daubechies wavelet filters showed that for MIMO 4x4 the angular position “error” estimates are reduced by an order of magnitude or more compared to MIMO 2x2. As the speed of the carrier increases, the estimates of “errors” of the angular position increase. The possibility of reducing the signal-to-noise ratio at given probabilities of correct detection and false alarm through the use of wavelet transforms is shown, and also where the wavelet can reach 8.9 dB.

6. Conclusion

The use of MIMO radar with wavelet signal processing for the detection and estimation of coordinates of small-sized ground objects is a promising and evolving field within radar technology and signal processing. MIMO radar systems offer significant advantages over traditional radar systems in terms of spatial diversity, resolution, and target detection capabilities. The use of multiple antennas at both the transmitter and receiver enables improved target detection, especially for small-sized objects. Wavelet signal processing techniques have been explored as a means to enhance radar performance. Wavelets offer benefits such as noise reduction, feature extraction, and improved signal-to-noise ratio, which are essential for detecting and estimating small targets in cluttered environments. MIMO radar, when combined with wavelet processing, can provide high spatial and temporal resolution. This is crucial for accurately estimating the coordinates of small-sized ground objects, even in scenarios with closely spaced targets.

REFERENCES

[1] X.J. Zhang, W. Jia, X.M. Guan, G.Q. Xu, J. Chen and Y.B. Zhu. 2019. Optimized deployment of a radar network based on an improved firefly algorithm, *Frontiers of Information Tech. & Electronic Engg.*, 20(3), 425-437. https://doi.org/10.1631/FITEE.1800749.

[2] E.L. Merle, D. Hauser and C. Tison. 2019. Directional wave spectra at the regional scale with the KuROS airborne radar: comparisons with models, *Ocean Dynamics*, 69(6), 679-699. https://doi.org/10.1007/s10236-019-01271-5.

[3] S.P. Rajan and C. Vivek. 2019. Analysis and design of microstrip patch antenna for radar communication, *J. Electrical Engg. and Tech.*, 14(2), 923-929. https://doi.org/10.1007/s42835-018-00072-y.

[4] M. Liu, L. Zou, H. Ren, X. Yu, Y. Zhou and X. Wang. 2021. A novel MIMO array with reduced mutual coupling and increased degrees of freedom, *Mathematical Problems in Engg.*, 2021. https://doi.org/10.1155/2021/3703657.

[5] J. Gong and Y. Guo. 2020. A bistatic MIMO radar angle estimation method for coherent sources in impulse noise background, *Wireless Personal Communications*, 116(1), 3567-3576. https://doi.org/10.1007/s11277-020-07865-3.

[6] J. Li and P. Stoica. 2009. MIMO Radar Signal Processing, *Wiley-IEEE Press*. https://doi.org/10.1002/9780470391488.

[7] Y. Zhu, G. Li, R. Wang, S. Tang and K. Cao. 2021. Intelligent fault diagnosis of hydraulic piston pump based on wavelet analysis and improved alexnet, Sensors, 21(2), 549. https://doi.org/10.3390/s21020549.

[8] C. Shi, F. Wang, S. Salous and J. Zhou. 2019. Joint subcarrier assignment and power allocation strategy for integrated radar and communications system based on power minimization, *IEEE Sensors J.*, 19(23), 11167-11179. https://doi.org/10.1109/JSEN.2019.2935760.

[9] G. Lv, J. Yang, N. Li, D. Hu, Y. Zhang and F. Zhao. 2018. Dielectric characteristics of unsaturated loess and the safety detection of the road subgrade based on GPR, *J. Sensors*, 5185460. https://doi.org/10.1155/2018/5185460.

[10] N. Tong, Y. Zhang, G. Hu, X. He and X. Hu. 2016. Multiple-input-multiple-output radar super-resolution three-dimensional imaging based on a dimension-reduction compressive sensing, *IET Radar, Sonar & Navigation*, 10(4), 757-764. https://doi.org/10.1049/iet-rsn.2015.0345.

[11] F. Hoffmann, M. Ritchie, F. Fioranelli, A. Charlish and H. Griffiths. 2016. Micro-Doppler based detection and tracking of UAVs with multistatic radar, *Proc. IEEE Radar Conf.*, Philadelphia, PA, USA, 1-6. https://doi.org/10.1109/RADAR.2016.7485236.

[12] P. An, B. Ng and H.T. Tran. 2016. Kurtosis-based estimation of cross-range scaling factor for high-resolution inverse synthetic aperture radar imaging, *J. App. Remote Sensors,*10(3). https://doi.org/10.1117/1.JRS.10.030502.

[13] S. Ding, N. Tong, Y. Zhang, X. Hu and X. Zhao. 2020. Cognitive MIMO imaging radar based on doppler filtering waveform separation, *IEEE Trans. Geosci. Remote Sensors,* 58, 6929-6944. https://doi.org/10.1109/TGRS.2020.2977967.