ISSN 2229-5518

Modeling, Simulation & Analysis of the Applicability of Wavelet Transform Technique for Automotive Radar Signal Processing

Nathaniel U. Nathaniel, Evans C. Ashigwuike, Umar I. Sadiq

Abstract– One of the applications of radar sensor is in vehicles: future technology has proposed self-driven vehicles. The radar sensor is to be used in detecting obstacles and providing accurate information about the vehicle's ambient environment, so as to activate appropriate control commands. This sensor will also need a computing platform that can ensure real-time processing of the received signals. Previous works encounter problems in the areas of having appropriate algorithm, chip-set, memory, etc. that are capable of performing these tasks sufficiently.

In this work, i. Radar Sensor signals is modeled and simulated – in terms of Waveform, Antenna (transmitter and receiver) and Propagation (Waveform Radiation & Collection) models, etc. ii. Radar signal for automated driving is simulated using Fast Fourier Transform (FFT) Technique. iii. Analysis on the FFT Technique used is made; in terms of its merits and demerits in this application. iv. Recommendations are made for the use of Wavelet Transform (WT) Technique for Processing of Automotive Radar Signals (ARS) by offering WT Technique Solutions to FFT Problems for ARS by modeling and simulating the following: (a) 1-D Multi-signal WT Operations; (b) Solution to the Noise Problems – Wavelet Denoising; (c) Use of WT for Time-Frequency Reassignment and Mode Extraction with Synchrosqueezing; (d) Discrete Wavelet Transform (DWT) and Continuous Wavelet Transform (CWT) of an ARS with a Frequency Break. All simulations are done using the MATLAB R2017b software.

This work will help in creating a more suitable algorithm that process radar sensor signal for self-driven vehicles. It has shown a comprehensive analysis of existing Automotive Radar Signals Processing (ARSP) systems using FFT technique and how WT technique could be applied for the same application, to overcome some of the major set-backs of the FFT technique. From this research, I have found out that the major problems with the self-driven vehicle technology using radar sensor are in the areas of appropriate algorithm**,** capable chip-set and sufficient memory; to carry out the task and meet-up with the real-time processing requirement of this application. My work is focused on the area of appropriate algorithm: to show how the WT technique and which of its tools, and how those tools could be used in developing appropriate algorithm for ARSP as applied in self-driven vehicles. The overall aim of this work, which is towards providing safer transportation with less human effort, will be achieved**.**

Index Terms— Automotive Radar, Automotive Radar Signal Processing, Fast Fourier Transform, Frequency Modulated Continuous Wave, Modeling, Signal Processing, Simulation, Wavelet Transform.

1 INTRODUCTION

Development of radar systems emerged in the early twentieth centuries, with designs for military and commercial applications: such as air defense purposes—long-range air surveillance, detection of targets, weather studies and forecasting, air traffic control, etc. [1]. Modern applications of radars in the automotive industry include providing parking assistance, lane departure warning, etc. to the driver. In [2], a proposal of self-driven cars considers an extended application of the radar in the automotive industry, whereby cars will have autonomous control of themselves; requiring very little or no assistance from the human passenger using it. In [2], consecutive radar scanning happen without any time interval between them; this is not necessary – the models used in this work has provided adequate timing between consecutive radar scanning to alleviate the memory overflow problems. Also, the accuracy of the results is limited by the range, velocity and angular resolution which are determined by the specific parameters of the RF front-end and the designed waveform pattern; the real-time performance on the architecture cannot be achieved due to the high latencies introduced by the memory transpose operations.

For actuators of these controls to function, they must have accurate information of the ambient and on time. This control information will be provided by radar sensors. Radar sensor is most preferred in this application (than infrared, Bluetooth, sonar, lidar, etc.) because of its range of coverage, it is less affected by the weather conditions, its construction and implementation can be made such that the effect of the sensor to the vehicle's aerodynamics and appearance is not detrimental, [3], [4].

Radar sensors use Frequency Modulated Continuous Wave (FMCW) radar to reliably detect moving or stationary targets. Radars that use rectangular pulse waveform are larger and are suitable for military applications; they have long distance target detection coverage. FMCW radars are smaller, use less power, and are much cheaper to manufacture compared to pulsed radars – they are used in smaller distance applications, about 200m coverage which is enough for automotive application. In processing the radar sensor signals, some of the issues with the FFT technique as captured from reviewed literatures, are the basis of the necessity for the proposal of the use of the WT technique for this application: it is shown that WT technique will overcome most of the FFT technique demerits.

The software for this work, MATLAB R2017b is preferred because of its vast capabilities and flexibilities for designs and simulations required: this version is more suitable because of the inclusion of the most needed toolboxes such as; Phased Array System Toolbox, Automated Driving System Toolbox, etc. which are not present in earlier releases. These products are involved mostly in the designs and simulations: *MATLAB and Simulink, Automated Driving System Toolbox, Phased Array System Toolbox, Wavelet Toolbox, Antenna Toolbox, Communications System Toolbox, DSP System Toolbox, Signal Processing Toolbox,* etc.

The main objectives of this work include: (i) to show how Automotive Radar Sensor Signal is processed using FFT technique; (ii) to analyze critically FFT technique as used for this application; (iii) to show the merits and demerits of using FFT technique for this application; (iv) to show how applicable and propose WT technique for this same application. This work will help in creating a more suitable algorithm that process radar sensor signal for self-driven vehicles.

1.1 Fundamentals of Radar Signal Processing

The efficiency of the self-driven vehicle system is based on its performance in terms of target detection and identification; which in turn is dependent on the information extracted from the sensor signal (a time domain signal): so it is crucial to adopt a more suitable transformation technique which is best to extract the relevant information from the signal. The received signal has some important information relating to the ambient, hidden in it and cannot be used directly by actuators in this application. Transformation techniques like the Wavelet transform, Fourier transform, Laplace transform and Z transform; are used to reveal this information.

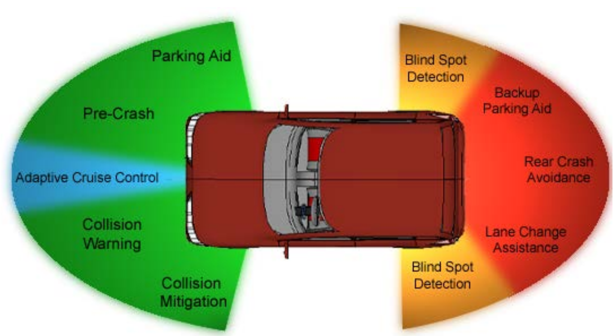


Fig. 1. Services Requiring Radar Signal Processing. The services listed, require accurate Radar Signal Processing, in order to give accurate information to actuators, to give appropriate control commands.

form, ile by ency, been transform, the similarity and dissimilarity of the target's signature can easily be observed. To get better information, the right transformation technique should be used [3]. Radar Signal Processing is required for the services in Fig. 1 above, to be provided in automotive application.

1.2 The Fourier Transform (FT)

FT is normally used to find the frequency content of a signal; for a signal $x_a(t)$, its FT, $X_a(\omega)$ is given by equation 1 below:

$$\mathbf{X}_{\boldsymbol{a}}(\boldsymbol{\mathcal{W}}) = \int_{-\infty}^{\infty} \boldsymbol{\mathcal{X}}_{\boldsymbol{a}}(\boldsymbol{t}) \boldsymbol{e}^{-\boldsymbol{j\omega t}} \boldsymbol{dt} \qquad (1)$$

If the FT of a signal in time domain is taken, the frequency-amplitude representation of that signal is obtained. FT and WT are reversible transforms; they allow going back and forward between the raw and processed (transformed) signals: only either of them is available at any given time. That is, no frequency information is available in the time-domain signal, and no time information is available in the Fourier transformed signal. FT gives the frequency information (spectral components) of the signal only, no more no less; it tells us how much of each frequency exists in the signal, but does not tell us when in time these frequency components exist - this information is required applications such as this, where the signal is not stationary. Stationarity is of paramount importance in signal analysis: stationary signals are those whose frequency content does not change in time; one does not need to know at what times frequency components exist, since all frequency components exist at all times. Non-stationary signals are those whose frequency components change continuously-do not appear at all times.

FT is not a suitable technique for non-stationary signal except if we are only interested in what spectral components exist in the signal, but not interested where these occur. If we want to know what spectral component occurs at what time (interval), i.e. when the time localization of the spectral components is needed, a transform giving the Time-Frequency Representation of the signal is needed - the ultimate solution is the WT, [5], [11] – [15].

1.3 The Wavelet Transform (WT)

WT was developed to overcome some resolution related problems of the FT; it is capable of providing the time and frequency information simultaneously, hence giving a time-frequency representation of the signal [5]. For non-stationary signal, such as the type for our application here, the Wavelet Technique is more suitable to be used: it gives a better time and frequency resolution a.k.a. multi-resolution. WT covers all the hidden information (scale and variation) obtained from FFT and gives more specific information of the non-stationary targets. WT is the transformation from FFT signal as it provides the time-frequency representation. Time and frequency can be providing simultaneously, therefore giving a time-frequency representation of the signal. Recall Heisenberg uncertainty principle, which states that the momentum and the position of a moving particle cannot be known simultaneously – it is applicable here; the frequency and time information of a signal at some certain point in the time-frequency plane cannot be known. The best we can do is to investigate what spectral components exist at any given interval of time. This is a problem of resolution, and it is the main reason why researchers have switched to WT. WT gives a variable resolution as follows: higher frequencies are better resolved in time (with less relative error), and lower frequencies are better resolved in frequency, [5] – [8]. Wavelet has two techniques or transformations that can be applied depend on the signal behavior – Discrete Wavelet Transforms (DWT) and Continuous Wavelet Transforms (CWT). Both of the techniques can be used for windowed, filtering, denoising, reconstruct, decomposing, extraction and compression. The CWT uses a continuous-time function which it divided into wavelets. It holds the ability to construct a time- frequency representation of a signal that offers very good time and frequency localization [3], [21]. WT is a convolution of a signal s(t) with a set of functions which are generated by translations and dilations of a main function. The main function is known as the mother wavelet and the translated or dilated functions are called wavelets [21]. Mathematically, the CWT is given by equation 2 below:

$$\boldsymbol{W(a,b)} = \frac{\mathbf{1}}{\sqrt{\boldsymbol{a}}}\int \boldsymbol{S(t)\Psi}\left(\frac{\boldsymbol{t-b}}{\boldsymbol{a}}\right)\boldsymbol{dt} \tag{2}$$

Where, b is translation time, a is the dilation of the wavelet. If the mother wavelet is in complex, the CWT is also in complex valued function. Or else the CWT is real. The power spectrum for CWT is equal to squared magnitude of CWT ([W(a,b)]2) and it is application dependent which it depends on the type of mother wavelet used.

For DWT, the wavelets are sampled separately by any wavelet transform. The difference with the Fourier Transform is it has time-based resolution which it captures both frequency and location time. The DWT of a signal x is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response g resulting in a convolution of the two. See equation 3 below:

$$\boldsymbol{y[n] = (x * g)[n] = \sum_{\kappa=-\infty}^{\infty} x[\kappa]g[n-k]} \tag{3}$$

The signal x is also decomposed simultaneously using a high-pass filter g. The outputs giving the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass): these two filters are related to each other and known as a quadrature mirror filter [22]. For every transformation of wavelet (DWT or CWT), they are using mother wavelets to function and evaluate. There are several types of mother wavelets which are Haar, Daubechies, Symlets, Meyer, Morlet, Gaussian, Shannon and Mexican Hat, etc.

1.4 How Radar Determine Range and Velocity of Targets

Basically, how does Radar determine range and velocity of targets accurately, even in the presence of noise? If we create a signal to transmit and simulate return signals, adding noise and Doppler shift and detect returned burst with Matched filter. Time delay in the returned signal can be Utilize to determine range: performing spectral analysis and using Doppler Effect, velocity can be calculated. The radar transmitter sends out a burst signal which hits the target. The speed of the target shifts the signal according to the Doppler equation. The radar then receives the reflected signal.

For Range: the system measures time for the return signal to arrive; thus

Range = (1/2c) *T_d, where T_d = time delay. For Velocity: the system measures Doppler shift; thus

Velocity = (f_dc)/(2f_c), where f_c = frequency of radar f_d = Doppler frequency shift

The block diagram for Radar Processing is shown in fig. 2. below.

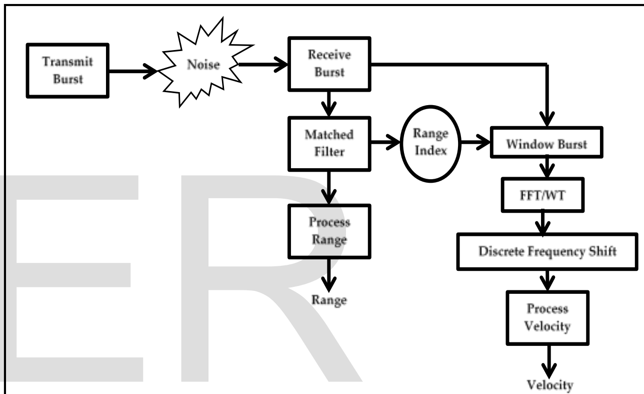


Fig. 2. Block Diagram for Radar Signal Processing.

To improve range accuracy, parameters can be refined; additional filtering could improve SNR [15].

In this work, **Modeling, Simulation and Analysis of Automotive Radar Signal Processing (ARSP) using FFT technique is carried out. The technique is analyzed critically, to show its merits and demerits in this application. Investigation and recommendations are made for the use of WT technique for this same application.** This work its self does not create any algorithm for automotive radar sensor signal processing but will greatly enhance the creation of such algorithms.

METHODOLOGY [Sections 2 & 3]

2. MODELING & SIMULATION OF ARSP WITH FFT

The work is fully shown in my Masters Theses: the following models are shown in full;

i. Basic Concept of End-to-End Radar System Design; ii. Modeling of Radar Sensor Detections; iii. Modeling of

Automotive Adaptive Cruise Control Using FMCW; iv. Modeling of Radar Sensor Signal Processing for Automated Driving [34] – [58]. The above models are used to show how to design, simulate and process radar signals for Automated Driving Applications: from those models, issues with the FFT technique as used in Automotive Radar Sensor Signal Processing are extracted; emphasize on, and show how to use WT technique to solve each particular problem.

Problems with the FFT techniques in ARS Application

2.1 Problems with FFT techniques (Deduced from the reviewed Literature and theoretical backgrounds).

(i) The FFT technique used in the algorithm causes the algorithm to require huge amount of intermediate data to be stored in a memory.

(ii) FT technique is not suitable for non-stationary signal, except if we are only interested in what spectral components exist in the signal, but not interested where these occur. But in this application, the time localization of the spectral components is needed, a transform giving the Time-Frequency Representation of the signal is needed.

(iii) The FT technique has some resolution related problems; it cannot provide the time and frequency information simultaneously, as required in this application.

2.2 Problems with FFT technique (Deduced from Simulations and Analysis)

(i) Poor position and velocity accuracy along the cross-range dimension

Caused by: resolution and noise problems.

(a) The longitudinal and lateral position errors are functions of the way the FFT process the received signals; in terms of handling the noise content and resolution issues. Radar reports lateral position accuracies as small as 0.06 meters at close ranges and up to 5.5 meters when the target is far from the radar.

(b) When the passing car enters the radar's field of view, the passing car's noise is initially large. The ego vehicle's radar inflates its reported 2σ longitudinal velocity noise to indicate its inability to observe the passing car's non-radial velocity components as it passes the ego vehicle.

(c) The inability of the ego vehicle radar to measure lateral velocity produces a large error during the passing car's lane change maneuver. The radar reports a large 2σ lateral velocity noise to indicate that it is unable to observe velocity along the lateral dimension.

(d) Range Doppler Coupling Effect, a range error of 1.14 m can no longer be ignored and needs to be compensated – it reduces the radar's capability of unambiguously detecting high speed vehicles; even the triangle sweep pattern recommended, cannot solve this problem totally.

(ii) Shorter detection ranges for pedestrians and other nonmetallic objects

Caused by: resolution problem, time-frequency issue and noise problems. The effect of an object's RCS on the radar's ability to "see" that object; cause poor detection of pedestrians and other nonmetallic objects. The mid-range radar proposed could not solve this problem too.

(iii) Close range detection clusters pose a challenge to tracking algorithms

Caused by: resolution problems. Multiple detections appear when the target is at ranges less than 30 meters (the radar model compares the vehicle's dimensions with the radar's resolution)

(iv) Inability to resolve closely spaced targets at long ranges

Caused by: resolution problems. After the distance between the radar and the motorcycles has increased, both motorcycles occupy the same radar resolution cells and are merged. The centroiding of the merged detections produces a -0.8m lateral bias corresponding to half of the distance between the motorcycles, all of the merged detections have this -0.8m bias.

3. MODELING & SIMULATION OF ARSP WITH WT

Modeling WT Technique Solutions to FFT Problems for ARS: the following are considered; (a) Modeling of 1-D Multi-signal WT Operations, (b) Modeling the Solution to the Noise Problems – Wavelet Denoising, (c) Modeling the use of WT for Time-Frequency Reassignment and Mode Extraction with Synchrosqueezing, (d) Modeling DWT and CWT of an ARS with a Frequency Break.

3.1 WT Technique Solutions to FFT Problems for ARS (Deduced from the reviewed Literature and theoretical backgrounds).

By adopting WT Technique for the signal processing algorithm, problems described in **A** (ii) & (iii) are solved. One way of solving the problem of **A** (i) is by employing the (very reliable and efficient tools) 1-D Wavelet operations; denoising-compressing-clustering: the model and simulation are discussed in section III below. The efficiency is gotten by the capacity of wavelet representations to concentrate signal energy in few coefficients. The fact that the third operation, Clustering, offers a convenient procedure to summarize a large set of signals using sparse wavelet representations, when used in the ARSP algorithm will reduce the amount of intermediate data to be stored in a memory during operation.

3.1.1 Modeling and Simulation of 1-D Multisignal WT Operations

Signals of same length stored as matrix organized rowwise or columnwise is referred to as 1-D multisignal: this model ***analyze***, ***denoise*** and ***compress*** a multisignal, and then ***cluster*** different representations or simplified versions of the signals composing the multisignal. The signals are first analyzed and simplified versions (Reconstructed approximations at given levels, Denoised versions, Compressed versions) are produced [59] - [60]. In WT, denoising and compressing are used as a preprocessing step before clustering. To summarize a large set of signals using sparse wavelet representations, several clustering strategies and comparison will be performed.

(i) Let's load and plot an example multisignal representing an ARS, to **analyze** it;
(ii) In 3-D, the individuality of the signals can be highlighted (giving a surface representation of the signals);
(iii) Next, is to carry out multisignal row decomposition at level 7 using sym4 wavelet;
(iv) After decomposition, let's reconstruct the approximations for each row signal and display two plots to compare the approximations (at level 7) with the original signals;
(v) A closer comparison, from iv above can be obtained by superimposing the original multisignal with their corresponding approximations (say first four and then last five);
(vi) **Denoising** the multisignal by WT technique is done by; **Decomposition** (choosing a wavelet and a level of decomposition N, and then compute the wavelet decompositions of the signals at level N). **Thresholding (**for each level from 1 to N and for each signal, a threshold is selected and thresholding is applied to the detail coefficients). **Reconstruction** (computing wavelet reconstructions using the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N). Decomposing at level 5;
(vii) **Compressing** the multisignal by WT technique is done by three steps as in denoising above, the difference is in the thresholding – giving rise to two compression approaches:
-Taking the wavelet expansions of the signals and keeping the largest absolute value coefficients (by setting a global threshold, a compression performance, or a relative square norm recovery performance, only a single signal-dependent parameter needs to be selected).
-Applying visually determined level-dependent thresholds.
Using level 7 decomposition (to make more efficient the compression and simplify the data representation) each row of the multisignal is compressed by applying a global threshold, this will lead to energy recovery of 99%;
(viii) To check compression performance, let's compute the corresponding densities of nonzero elements in the multisignal;
(ix) A convenient procedure to summarize a large set of signals using sparse wavelet representations is by **Clustering**; in MATLAB, the function – '*mdwtcluster*' is used to implement hierarchical clustering. The number of clusters is set to 3; structures P1 and P2 which contain respectively the two first partitions and the third one, are compute: the equality of the three partitions are then tested.
(x) Next is to display the original signals and the corresponding approximation coefficients used to obtain two of the three partitions.

3.1.2 Simulation, Results and Discussion

i. From the modeling above, Fig. 3. (a) below, is obtained: the signals are irregular and noisy.

ISSN 2229-5518

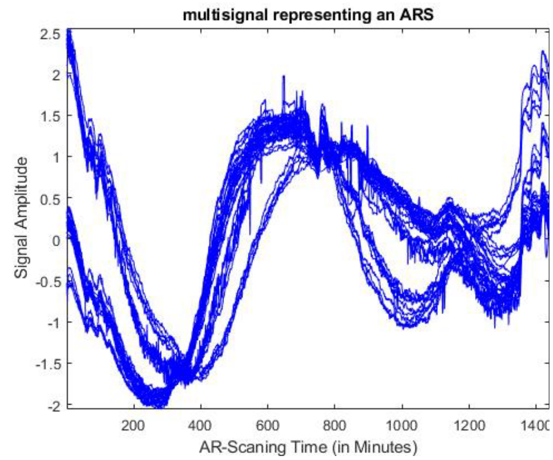


Fig. 3 (a). multi-ARS Plot.

ii. Individual signals can be seen more clearly, Fig. 3 (b).

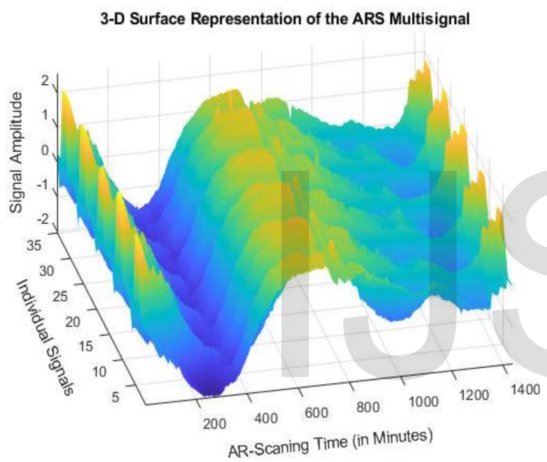


Fig. 3 (b). Surface Representation of multi-ARS in 3-D.

iii. Multisignal row decomposition structure is shown on workspace when simulating the code.

iv. Figures 3 (c-i) shows all the original multisignal and (c-ii) shows all the corresponding approximations.

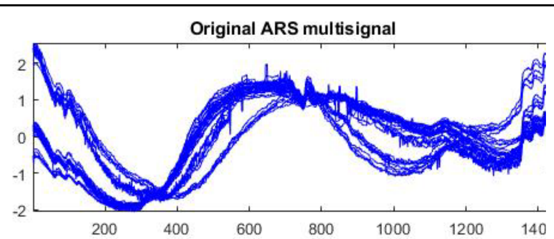


Fig. 3 (c) i. original multisignal

The approximations only capture the general shape some interesting features are lost; see that the bumps at the beginning and at the end of the signals are not there in the approximations.

v. The original multisignals superimposed with their corresponding approximations are shown in figures 3 (d); (i) shows the first four signals (ii) shows the last five signals.

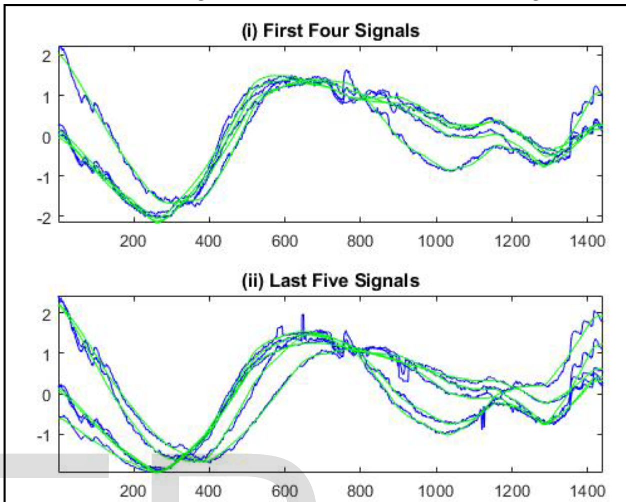
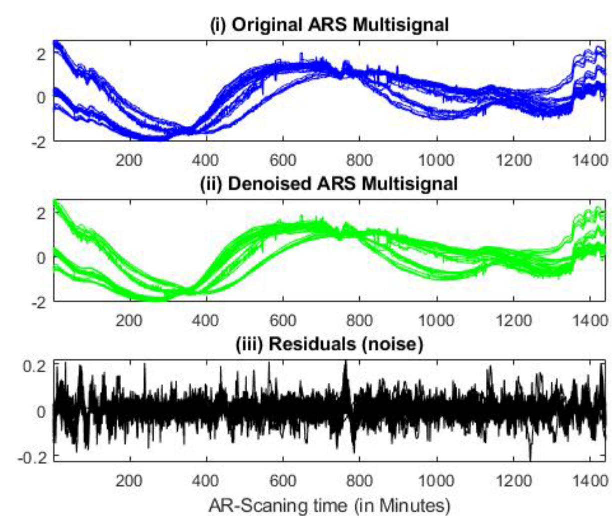


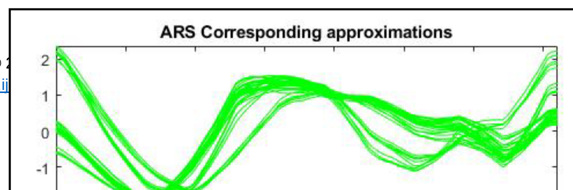
Fig. 3 (d). original multisignals superimposed with their corresponding approximations

As can be seen, the approximation (Green) of the original signal (Blue) is visually accurate in terms of general shape.



Figures 3 (e) i – iii – Denoising the AR-multisignal

vi. the bumps at the beginning and at the end of the (original) signals are recovered (denoised signals) and the residuals (noise) look like a noise. Minor remaining bumps (with a very small order magnitude) are due to the signals.



ISSN 2229-5518

vii. After compression using level 7 decomposition, see that in figures 3 (f) i - iii, the general shape of the multisignal is preserved while the local irregularities are neglected.

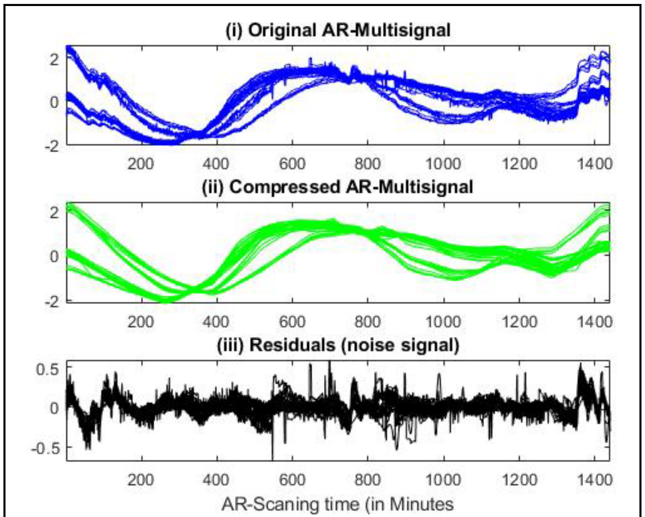


Fig. 3 (f) i– iii. Compressing the AR-multisignal.

viii. The percentage of required coefficients to recover 99% of the energy lies between 1.25% and 1.75%, wavelets have a way to concentrate signal energy in few coefficients for each signal, figure 3 (g).

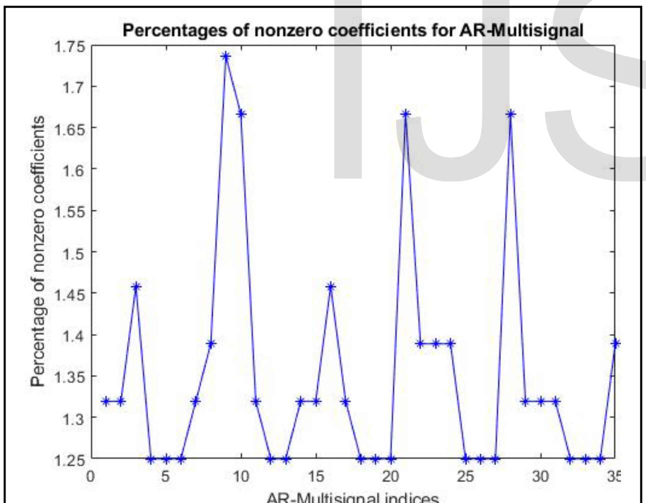


Fig. 3 (g). densities of nonzero elements in the multisignal

ix. After clustering the multisignal, figure 3 (h), Comparing the three different clusterings of the multisignal: cluster one is based on the original multisignal, cluster two is based on the approximation coefficients (level 7), cluster three is based on the denoised multisignal.

The code line *"EqualPART = isequal(max(diff(Clusters,[],2)),[0 0])"* test the equality of the three partitions, returning *"EqualPART = logical 1"*. Meaning that the three partitions are the same. Interpreting figure 3 (h) above, cluster 3 contains 25 (middle) multisignals; cluster 2 contain five second-to-last group of the multisignal; and 1 contain the five last group of the multisignal. Illustrating the periodicity of the underlying time series and the three different general shapes seen in figures 3 (a) and 3 (b).

x. By displaying the original signals and the corresponding approximation coefficients used to obtain two of the three partitions, figure 3 (i), it can be seen that the same partitions are obtained from the original multisignal and from the coefficients of approximations: meaning that that using less than 2% of the coefficients is enough to get the same clustering partitions of that group of AR-multisignal.

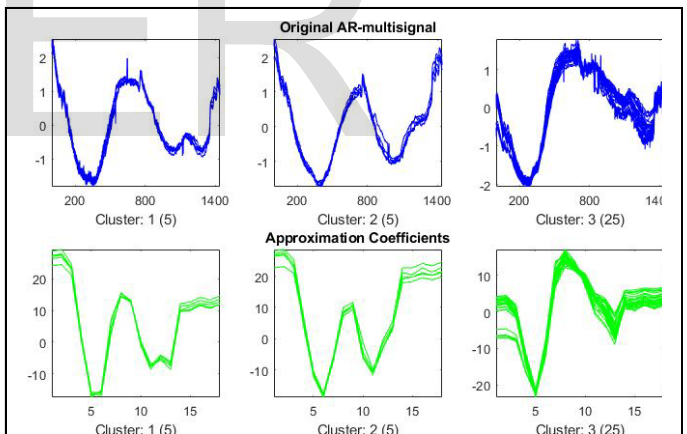
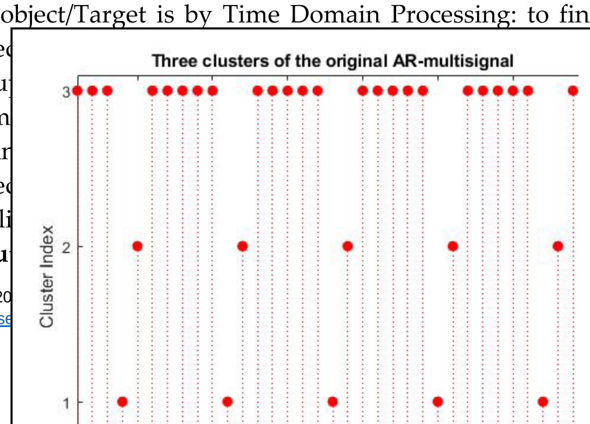


Fig. 3 (i). Original signal and approximation coefficients for the three partitions

3.2 WT Technique Solutions to FFT Problems for ARS, (Deduced from Simulations and Analysis)

From reviewed literatures we found out that to find range of the object/Target is by Time Domain Processing: to find the spee[...] tion, to su[...] ency Dom[...] FFT techn[...] sing, espe[...] this appli[...] **, the Solu[...]** in all



ISSN 2229-5518

four categories of the FFT problems in this application are caused by the way Time and Frequency Domain Processing are handled in the FFT technique.

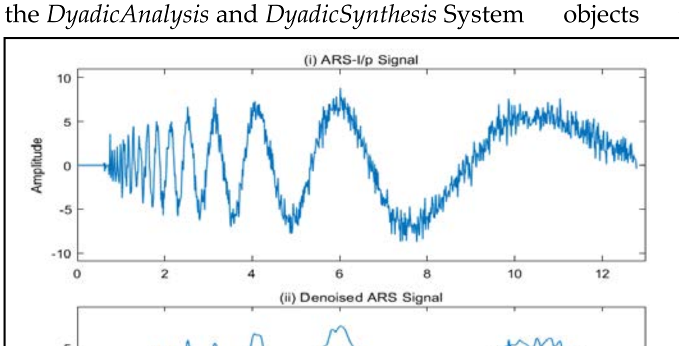
The ARS application deals with non-stationary signals; the time localization of the spectral components is needed, necessitating the availability of both the time and the frequency information at the same time, which can only be given by WT and not FT. This work has brought about key concepts that would be used in a new algorithm driven by the powerful WT technique: they will be modeled, simulate, analyzed and assigned to the FFT problems (Deduced from Simulations and Analysis), listed above.

3.2.1 Modeling the Solution to the Noise Problems – Wavelet Denoising

In [19], it is shown that one dimensional B-spline wavelet transform on the target impulse reduce the amount of data which must be stored for each aspect angle & strongly restrains the effect of additive Gauss white noises. The proposed WT technique will eliminate the effect of environmental noise which affects the ADAS potency in target detection and identification. The denoising strategy is as follows: - a threshold is chosen that separates the (smaller) noise wavelet coefficients from the (larger) wavelet coefficients corresponding to the singularities; - below this threshold, the wavelet coefficients are set to zero (this is called hard thresholding) [23].

From the model and simulation, we extract the following issues which are peculiar to the FFT algorithm used. the CFAR detector used to identify detections in the processed range and Doppler data only estimate the background noise level of the received radar data. At locations where the signal power exceeds the estimated noise floor by a certain threshold, detections are found; low threshold values result in a higher number of reported false detections due to environmental noise. Increasing the threshold produce fewer false detections, but also reduces the probability of detection of an actual target in the scenario.

This constitutes a minus for the FFT technique in this application: using the WT technique, the issue can be solved by employing a suitable denoising technique. A requirement here is to develop a WT-based signal processing chain, similar to the FFT-based described; as one of the key problems solved in this work, we'll model how this problem is handled using a WT-based denoising technique. Let's also clear a doubt here that the algorithm provides an estimate with very little or no delay. This model shows how to use the *DyadicAnalysis* and *DyadicSynthesis* System objects to



g
st
e,
he
ds

and lower values for low frequency sub-bands, [59], [60]. Two things to be done, we'll initialize the System objects and then stream processing loop.

In Initializing the System object, first, to obtain optimal performance, it is crucial that we create and initialize the System objects before they are used in a processing loop; second, create a SignalSource System object to output the noisy signal; third, create and configure a *DyadicAnalysisFilterBank* System object for wavelet decomposition of the signal; forth, create three Delay System objects to compensate for the system delay introduced by the wavelet components; fifth, create and configure a *DyadicSynthesisFilterBank* System object for wavelet reconstruction of the signal; lastly, we create time scope System object to plot the original, denoised and residual signals. In streaming the processing loop, we create a processing loop to denoise the input signal; this loop uses the System objects instantiated above.

Another issue with target identification is object's *electrical* size; which depends on the object's size, shape, the kind of materials it contains and transmits frequency of the radar. Its value is large for metallic objects like vehicles and small for nonmetallic objects like pedestrian; autonomous driving system radar must be able to generate detections on both of these object classes – which is possible only with a better signal processing algorithm. Using wavelet synchrosqueezing (to obtain a higher-resolution time-frequency analysis), these problems may be solved – it involves extracting and reconstructing oscillatory modes in a signal.

3.2.2 Simulation, Results and Discussion

I use signal processing System objects *DyadicAnalysisFilterBank* and *DyadicSynthesisFilterBank* to denoise the noisy automotive radar signal using user-specified thresholds. The Input Signal window of Fig. 4 (i) shows the original noisy signal, the Denoised Signal window of Fig. 4 (ii) shows the signal after suppression of noise, and the Residue Signal window of Fig. 4 (iii) displays the error between the original and denoised signal. By using the user-specified thresholds, one can configure the denoising to suite a particular automotive radar characteristics and parameters.

By incorporating appropriate WT denoising technique, in the algorithm, the issues listed in this section is solved; also the problem of detection of closely spaced targets. [61] - [63] give more strategic denoising techniques with WT; which depends on the application. This model Enhanced Target Detection and identification and other noise related issues.

3.2.3 Solutions to the Resolution Problem

An ARSP algorithm must contain techniques to resolve resolution issues in the radar sensor for effective operations. So, what are the probable causes of the resolution problem? What tools can the WT technique offer and how can those tools be used to offer solutions to identified resolution problems? ***WT offers <u>Synchrosqueezing</u> which can compensate for the spreading in time and frequency caused by linear transforms like the FFT, STFT, etc. this is achieved by <u>sharpening time-frequency analysis</u>. The higher resolution will be obtained by sharpening time-frequency analysis. Frequency Break and the inability of the FFT to evaluate it also causes poor Resolution in the signal processing algorithm. WT offers CWT and DWT as tools to solve this: this work also show how these tools are utilized.***

3.2.4 Modeling the use of WT for Time-Frequency Reassignment and Mode Extraction with Synchrosqueezing

One way of solving the resolution problems is by employing this operation. wavelet synchrosqueezing is used to obtain a higher resolution time-frequency analysis this will compensate the radar sensor resolution used in such application. Mode extraction from the synchrosqueezing transform is used to isolate signal components, which are impossible to isolate with conventional bandpass filtering. In practice, ARS consist of a number of oscillatory components, or modes - which exhibit slow variations in amplitude and smooth changes in frequency over time. Signals consisting of such components are also referred to as Intrinsic Mode Functions (IMF). Signals consisting of a sum of well-separated IMFs can be analyzed with Wavelet synchrosqueezing – by sharpening the time-frequency analysis of the signal as well as reconstruct individual oscillatory modes for isolated analysis [64] – [66]. The FFT cannot perform this operation – the CWT would do it but Wavelet synchrosqueezing is better. The higher resolution will be obtained by sharpening time-frequency analysis. WT offers Synchrosqueezing which can compensate for the spreading in time and frequency caused by linear transforms like the STFT, FFT, etc. Time frequency analysis depends on the intrinsic time-frequency properties of the signal, also on the properties of the wavelet [67] – [72].

In this model [sharpen time frequency analysis], a CWT of an example ARS is loaded;

CASE 1:

Signal's frequency begins at 1KHz at t = 0,
Signal's frequency decreases to 0.22KHz at t=2,
Signal's frequency increases back to 1KHz at t=4,
Using a sampling frequency of 2KHz.
Note that in this model, the CWT is used as a measuring device.

CASE 2:

Signal's frequency begins at 1KHz at t = 0,
Signal's frequency decreases to 0.22KHz at t=2,
Signal's frequency increases back to 1KHz at t=4,
Using a sampling frequency of 2KHz.

3.2.5 Simulation, Results and Discussion

CASE 1: **Sharpen Time-Frequency Analysis – CWT of an example ARS**

From figure 5 (a), the energy of the example ARS is smeared in the time-frequency plane by the time-frequency concentration of the wavelet. If the time-frequency concentration of the CWT magnitudes is focused on near 0.22KHz, it is seen that it is narrower than that observed near 1KHz. This is not an intrinsic property of the Loaded example ARS but an artifact of CWT, the measuring device.

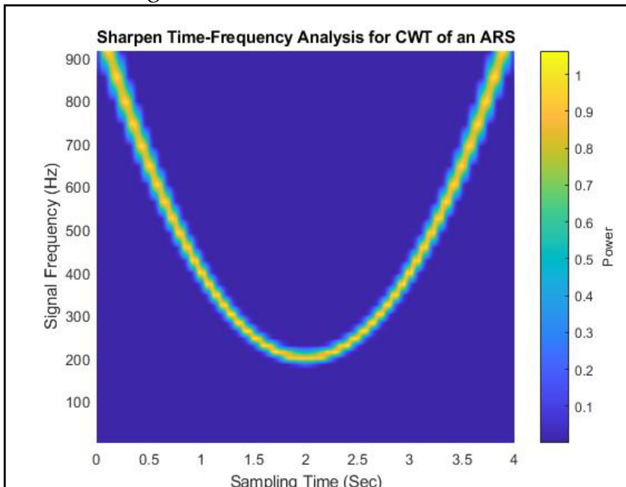


Fig. 5 (a). CWT of an ARS

CASE 2: **Sharpen Time-Frequency Analysis – synchrosqueezed transform**

Compare (CASE 1) the time-frequency analysis of the same signal obtained with the synchrosqueezed transform (CASE 2).

ISSN 2229-5518

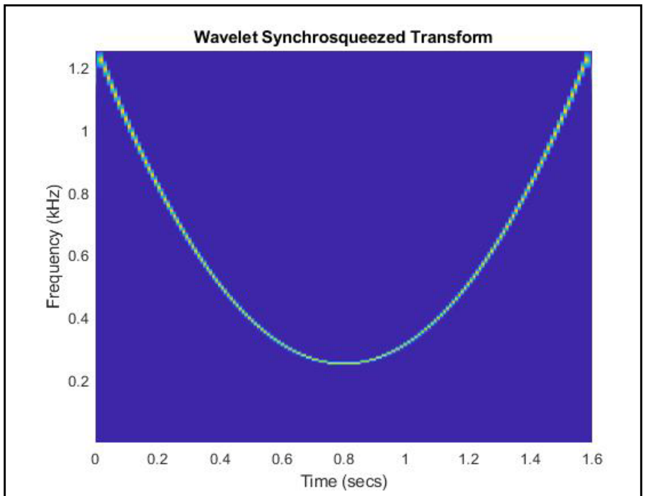


Fig. 5 (b). Synchrosqueezed transform for CWT of an ARS

In figure 5 (b), the synchrosqueezed transform uses the phase information in the CWT (figure 5 (a)) to sharpen the time-frequency analysis of the example ARS. It is concluded that while FFT cannot give this resolution enhancement operation, … : and … hat is … solve … Close … nges … ction … ill be … range

… ith a

… lying … ssary to identify which methods will best solve a particular identified issue: Not all values of a decomposition are needed to exactly reconstruct the original signal when the energy of the signal is finite. Do you need to know all values of a continuous decomposition to reconstruct the signal exactly? If YES, then CWT is the answer; else it is DWT. A continuous-time signal is characterized by the knowledge of the discrete transform; in such cases, discrete analysis is sufficient and continuous analysis is redundant. Continuous analysis is easier to interpret, since its redundancy tends to reinforce the traits and makes all information more visible: the analysis gains in "readability" but not saving space [73]. This model shows a discontinuous ARS that consists of a slow sine wave abruptly followed by a medium sine wave: the ARS with frequency break is loaded and DWT at level 5 using Haar wavelet is performed. Then the CWT is performed, where the result can be visualized.

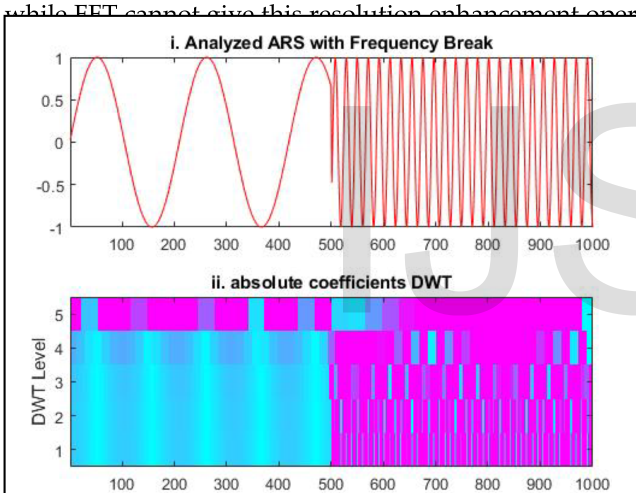
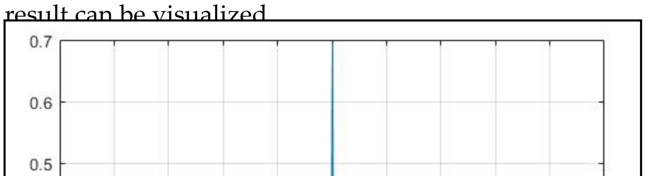


Figure 6 (a) – DWT of ARS with Frequency Break



3.2.7 Simulation, Results and Discussion

Analysis using wavelets can detect the exact instant when a signal changes: quite applicable for the problem of Shorter detection ranges for pedestrians and other nonmetallic objects, see figure 6 (a) and (b). At the CWT coefficient finest scale figure 6 (c), frequency change can be precisely localized. This concept is an important advantage of WT analysis over FFT: the instant when the signal's frequency changed is clearly observable with the CWT analysis. Same cannot be said of FFT, if the same signal had been analyzed by it – we would not have been able to detect the instant when the signal's frequency changed.

3.3 Uses of Radar Sensor Detections – Controls to Activate

The results of the detections are to be used in activating controls such as direction (steering), Movements (acceleration, Forward and Reverse movement), Speed (change gears, Deceleration), Indications (lightings, direction indicators, horn, alarms), etc.

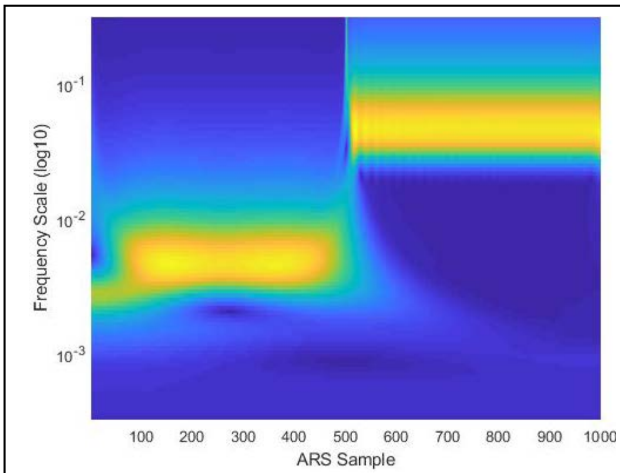


Fig. 6 (b). CWT of ARS with Frequency Break

4. CONCLUSION

This work has shown a comprehensive analysis of existing ARSP systems using FFT technique and how WT technique could be applied for the same application, to overcome some of the major set-backs of the FFT technique. From this research, I have found out that the major problems with the self-driven vehicle technology using radar sensor are in the areas of appropriate algorithm, capable chip-set and sufficient memory; to carry out the task and meet-up with the real-time processing requirement of this application. My work is focused on the area of appropriate algorithm: to show how the WT technique and which of its tools, and how those tools could be used in developing appropriate algorithm for ARSP as applied in self-driven vehicles.

The WT technique proposed in this work is still very new in this application; more works are required in the areas of coding, signal processing, simulation models, etc. Also, more should be done in analyzing the capabilities of the WT technique for this application.

5. ACKNOWLEDGEMENT

I wish to acknowledge the contribution of the following persons, to the success of this work: Prof. Okechukwu C. Ugweje, Dr. Umar Sadiq, Dr. Evans C. Also my Institution, Nile University of Nigeria; for a promised Research grant.

6. REFERENCES

[1] *O. C. Ugweje,* ***"Advanced Communication Systems"*** *Class notes for EEE602, Department of Electrical and Electronics Engineering, Nile University of Nigeria, Abuja, April, 2015.*

[2] *S. Suleymanov,* ***"Design and implementation of an FMCW Radar signal processing module for automotive applications"****, M.Sc. thesis, University of Twente, 2016.*

[3] *C. W. Fareez et al* ***"Forward Scattering Radar (FSR) Ground Target Signal Processing Using Wavelet Technique (WT)"*** *in Institution of Engineering and Technology IET International Radar Conference Hangzhou, China 14-16 Oct 2015.*

[4] *F. H. Sanders,* ***"Detection and Measurement of Radar Signals"****: A Tutorial, 7th Annual ISART, NTIA Institute for Telecommunication Sciences, 1 March 2005.*

[5] *R. Polikar* ***"The Wavelet Tutorial"*** *Second Edition, Part I— Fundamental Concepts & an Overview of the Wavelet Theory. 1996.*

[6] *R. Polikar* ***"The Wavelet Tutorial"*** *Second Edition, Part II— Fundamentals: the Fourier Transform and the Short Term Fourier Transform. 1996.*

[7] *R. Polikar* ***"The Wavelet Tutorial"*** *Second Edition, Part III— Multi-Resolution Analysis & the Continuous Wavelet Transform. 1996.*

[8] *R. Polikar* ***"The Wavelet Tutorial"*** *Second Edition, Part IV— Multi-Resolution Analysis: the Discrete Wavelet Transform. 1996.*

[9] *I. Daubechies, Y. Meyer & S. Mallat* ***"Basics of Wavelets"*** *Ten Lectures on Wavelets; Orthonormal Bases of Compactly Supported Wavelets.*

[10] *M. Misiti, et al* ***"Wavelet Toolbox"*** *For Use with MATLAB®.*

[11] *Jonas Gomes & Luiz Velho* ***"From Fourier Analysis to Wavelets"****. Instituto de Matematica Pura e Aplicada, IMPA Rio de Janeiro, Brazil*

[12] *S. Gilbert, & Nguyen, Truong.* ***"Wavelets and Filter Banks".*** *Wellesley, MA: Wellesley-Cambridge Press, 1996.*

[13] *Vaidyanathan, P. P.* ***"Multirate Systems and Filter Banks****". Englewood Cliffs, New Jersey: Prentice Hall PTR, 1993.*

[14] *T. L. Lee & Akio Yamamoto* ***"Wavelet Analysis: Theory & Application".*** *Hewlett-Packard Journal, December 1994.*

[15] *C. Sidney Burrus [et al.],* ***"Computer-Based Exercises for Signal Processing Using MATLAB",*** *1998.*

[16] *HOLLY MOORE* ***"MATLAB® for Engineers"****. Third Edition Salt Lake Community College. Salt Lake City, Utah. Library of Congress Cataloging–in–Publication Data. Moore, Holly. Copyright © 2012 Pearson Education, Inc., publishing as Prentice Hall, One Lake Street, Upper Saddle River, New Jersey 07458. MATLAB® for engineers / Holly Moore. — 3rd ed. p. cm. Includes index. ISBN-13: 978-0-13-210325-1 ISBN-10: 0-13-210325-7*

[17] *Georg Hanak & Dr. Ralph Mende "****Using FPGAs In Automotive Radar Sensors".*** *Product FAE Altera GmbH ghanak@altera.com Freisinger Strasse 3, 85716 Unterschleissheim, Germany & Managing Director smart microwave sensors GmbH, ralph.mende@smartmicro.de Mittelweg 7, 38106 Braunschweig, Germany www.smartmicro.de*

[18] *Meinecke, Marc-Michael; Rohling, Hermann: "****Waveform Design Principles for Automotive Radar Systems"****. German Radar Symposium, Berlin 2000.*

[19] *Ping Fan and Zhanrong Jing "****B-spline Wavelet-based Target Feature Extraction in Wideband Radar".*** *School of Electronics and Information, Northwestern Polytechnical University, Xi'an, Shaanxi Province, China. fanping2007@gmail.com*

[20] *H. Liu, L. Du, Y. Li, and Z. Bao, "Progress in radar automatic target recognition based on high range resolution profile", Journal of Electronics & Information Technology, vol. 27, pp. 1328–1134, August 2005.*

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

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

[23] *F. Chaplais "Wavelets and Signal Processing". Systems and Control Center, École des Mines de Paris.*

[26] *The MATLAB® Documentation:* ***"End-to-End Radar System".*** *MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2017 by The MathWorks, Inc.*

[27] *The MATLAB® Documentation:* ***"Motion Modeling in Phased Array Systems".*** *MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2017 by The MathWorks, Inc.*

[28] *The MATLAB® Documentation: **"Rectangular Pulse Waveforms"**. MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2017 by The MathWorks, Inc.*

[29] *The MATLAB® Documentation**: "Global and Local Coordinate Systems "**. MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2017 by The MathWorks, Inc.*

[30] *The MATLAB® Documentation: **"Transmitter".** MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2017 by The MathWorks, Inc.*

[31] *The MATLAB® Documentation: "Radar Equation". MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2017 by The MathWorks, Inc.*

[32] *The MATLAB® Documentation: "Receiver Preamp". MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2017 by The MathWorks, Inc.*

[33] *The MATLAB® Documentation: "Free Space Path Loss". MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2017 by The MathWorks, Inc.*

[34] *The MATLAB® Documentation: "Model Radar Sensor Detections". MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2017 by The MathWorks, Inc.*

[35] *The MATLAB® Documentation: "Sensor Fusion Using Synthetic Radar and Vision Data". MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2017 by The MathWorks, Inc.*

[36] *The MATLAB® Documentation: "Radar **Equation Calculator**". MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2017 by The MathWorks, Inc.*

[37] *The MATLAB® Documentation: "Driving Scenario Generation and Sensor Models". MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2017 by The MathWorks, Inc.*

[47] *The MATLAB® Documentation: **Automotive Adaptive Cruise Control Using FMCW Technology.** MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[48] *C. Karnfelt, et al. **"77 GHz ACC Radar Simulation Platform"**, IEEE International Conferences on Intelligent Transport Systems Telecommunications (ITST), 2009.*

[49] *The MATLAB® Documentation: "**FMCW Patch Antenna Array".** MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[50] *The MATLAB® Documentation: "Patch Antenna Array for FMCW Radar". MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[51] *The MATLAB® Documentation: **"Automotive Adaptive Cruise Control Using FMCW and MFSK Technology"**. MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[52] *H. Rohling, and M. Meinecke. "**Waveform Design Principle for Automotive Radar Systems**", Proceedings of CIE International Conference on Radar, 2001.*

[53] *The MATLAB® Documentation: **"Zoom FFT".** MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[54] *The MATLAB® Documentation: **"Radar Signal Simulation and Processing for Automated Driving".** MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2017 by The MathWorks, Inc.*

[38] *The MATLAB® Documentation: "Detection, Range and Doppler Estimation". MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2017 by The MathWorks, Inc.*

[39] *The MATLAB® Documentation: "birdsEyePlot". MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[40] *The MATLAB® Documentation: "**Visualize Sensor Coverage, Detections, and Tracks".** MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[41] *The MATLAB® Documentation: "**Driving Scenario Tutorial".** MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[42] *The MATLAB® Documentation: "**Create Actor and Vehicle Paths".** MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[43] *The MATLAB® Documentation: "**Doppler Estimation".** MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[44] *The MATLAB® Documentation: **"Waveform Design to Improve Performance of an Existing Radar System"**. MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[45] *The MATLAB® Documentation: "**Simulating a Bistatic Radar with Two Targets".** MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[46] *Richards, Mark. "**Fundamentals of Radar Signal Processing**". New York: McGraw Hill, 2005.*

[55] *The MATLAB® Documentation: **"Range Estimation Using Stretch Processing"**. MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[56] *The MATLAB® Documentation: "Signal Detection Using Multiple Samples". MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[57] *The MATLAB® Documentation: "Radar Data Cube". MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[58] *The MATLAB® Documentation: **"Constant False Alarm Rate (CFAR) Detection"**. MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[59] *The MATLAB® Documentation: **"Wavelet Denoising"**. MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[60] *The MATLAB® Documentation: **"Wavelet Reconstruction and Noise Reduction".** MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[61] *The MATLAB® Documentation: **"Wavelet Interval-Dependent Denoising"**. MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[62] *The MATLAB® Documentation: **"Multivariate Wavelet Denoising"**. MATLAB® and SIMULINK R2017b Documentation. The MathWorks,*

Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.

[63] *M. Aminghafari, N. Cheze and J-M. Poggi. "**Multivariate denoising using wavelets and principal component analysis**", Computational Statistics & Data Analysis, 50, pp. 2381-2398, (2006).*

[64] *The MATLAB® Documentation: **"Time-Frequency Reassignment and Mode Extraction with Synchrosqueezing".** MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[65] *I. Daubechies, Lu, J., and Wu, H-T. "**Synchrosqueezed wavelet transforms: an empirical mode decomposition-like tool.**" Appl. Comput. Harmonic Anal., 30(2):243-261, 2011.*

[66] *G. Thakur, Brevdo, E., Fuckar, N.S. and Wu H-T. "**The synchrosqueezing algorithm for time-varying spectral analysis: robustness properties and new paleoclimate applications.**" Signal Processing, 93(5), 1079-1094, 2013.*

[67] *S. Meignen, Oberlin, T., and McLaughlin, S. "**A new algorithm for multicomponent signals analysis based on synchrosqueezing: with an application to signal sampling and denoising.**" IEEE Transactions on Signal Processing, vol. 60, no. 12, pp. 5787-5798, 2012.*

[68] *The MATLAB® Documentation: **"Compare Time-Frequency Content in Signals with Wavelet Coherence"**. MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

[69] *X. Cui, Bryant, D.M., and Reiss. A.L. "**NIRS-Based hyperscanning reveals increased interpersonal coherence in superior frontal cortex during cooperation**", Neuroimage, 59(3), pp. 2430-2437, 2012.*

[70] *A. Grinsted, Moore, J.C., and Jevrejeva, S. "**Application of the cross wavelet transform and wavelet coherence to geophysical time series**", Nonlin. Processes Geophys., 11, pp. 561-566, 2004.*

[71] *D. Maraun, Kurths, J. and Holschneider, M. "**Nonstationary Gaussian processes in wavelet domain: Synthesis, estimation and significance testing**", Phys. Rev. E 75, pp. 016707(1)-016707(14), 2007.*

[72] *C. Torrence, and Webster, P. "**Interdecadal changes in the ESNO-Monsoon System**," J.Clim., 12, pp. 2679-2690, 1999.*

[73] *The MATLAB® Documentation: **"Continuous and Discrete Wavelet Analysis of Frequency Break"**. MATLAB® and SIMULINK R2017b Documentation. The MathWorks, Inc. MATLAB® Primer © COPYRIGHT 1984–2018 by The MathWorks, Inc.*

- *Nathaniel U. Nathaniel is currently pursuing masters degree program in Electrical Electronics Engineering, University of Abuja, P. M. B. 117 Abuja, Nigeria. Also working as Assistant Lecturer in the Department of Computer Engineering, Nile University of Nigeria Jabi, Abuja, Nigeria. Phone: +2348060799282, +2348182259811. E-mail: nathaniel@nileuniversity.edu.ng*

- *(Theses Supervisor) Dr. Evans C. Ashigwuike is the HOD, Department of Electrical Electronics Engineering, University of Abuja, P. M. B. 117 Abuja, Nigeria. Phone: 08036335397, 09096392069. E-mail: ecashigwuike@ymail.com*

- *(Theses Co-Supervisor) Dr. Sadiq I. Umar is a staff in National Space Research & Development Agency (NASRDA), Olusegun Obasanjo Space Center. Abuja, FCT Nigeria. & Lecturer in the Department of Electrical Electronics Engineering, University of Abuja, P. M. B. 117 Abuja, Nigeria. Phone: 08036472453. E-mail: sadiqumar2001@yahoo.com*