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Profiling radar signals based of pulse-to-pulse frequency agility

Ashraf A. Ahmad [1, *], Mustapha M. Aji [1], Yusuf Abdulmumin [1, 2], Ilyasu A. Jae [1] and Uthman I. Bello-Imokhuede [1]

[1] *Department of Electrical/Electronic Engineering, Nigerian Defence Academy, Kaduna, Nigeria.*
[2] *Department of Computer Science, Federal University, Dutsin-ma, Katsina, Nigeria.*

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Abstract

It is well known that the application of radar is becoming more and more popular with the development of signal technology progress. Therefore, this paper presents a first-stage process for radar signals analysis involving four different radar signals based on pulse-to-pulse frequency Agility. The radar signals include a normal radar signal (NRS), frequency hopping radar signal (FHRS), 2-frequency shift keying radar signal (2FSKRS), and a combination of frequency hopping radar signal (FHRS) and 2-frequency shift keying radar signal (2FSKRS). The process of modeling and generating the radar signals is presented and thereafter, results on the outcome of this process and their implications are discussed. It is observed from the obtained results of an accurate depiction of key parameters of pulse width (PW) of 1 µs and frequency of 10 MHz of the radar signals among others, that the developed models of the radar signals are feasible for further analysis using robust model signal processing tools such as time-frequency analysis can be used. Hence, these models can be used in practical radar signal analysis such as electronic intelligence (ELINT) and electronic warfare support (ES).

Keywords: Radar Signal; Hilbert transform; Frequency Agility; Electronic intelligence (ELINT); Electronic warfare support (ES)

1. Introduction

Radar, as a result of the continual advancement of radar technology, is widely used on the contemporary battlefield and has gradually risen to the position of becoming the primary technology in modern combat [1]. Systems used in military equipment, such as radar and communication systems, play crucial roles in modern warfare. One key area related to these systems is the field of electronic intelligence (ELINT) aspect of electronic warfare (EW) whose primary aim is the control of the electromagnetic spectrum for allowing of ally usage and denial of service to non-allies. ELINT can be defined as simply the interception and analysis of radar signals [2][3].

The generation and analysis of radar signal waveforms are accompanied by several challenges. Firstly, designing radar waveforms with specific characteristics, such as low probability of intercept (LPI), can be a complex task. Generating waveforms that are difficult to detect or intercept requires careful consideration of factors like modulation schemes, pulse shaping, and frequency agility [4]. Secondly, the analysis of radar signal waveforms involves dealing with various issues. One major challenge is the presence of noise in the received signals, which can degrade the accuracy of waveform analysis and identification. Techniques to mitigate the impact of noise, such as denoising algorithms or windowing methods, need to be employed.Additionally, the classification and recognition of radar signal waveforms require robust and efficient algorithms [5]. Overall, the challenges associated with the generation and analysis of radar signal waveforms include waveform design complexity, noise interference, complex time-frequency characteristics, and the development of robust classification algorithms. Addressing these challenges requires expertise in radar engineering,

*Corresponding author: A. A. Ahmad

signal processing, and algorithm development. As such, this research presents a solution to the first challenge of presenting radar signals waveform generation based on pulse-to-pulse frequency agility.

Various researches have been conducted in related to radar signal analysis, Earlier, some researchers introduced a method for recognizing low probability of intercept (LPI) waveforms using polytime coded radar signals [6]. The approach employed continuous wavelet transform (CWD) as the main time-frequency distribution (TFD) and utilized a convolutional neural network (CNN) as the classifier. To address computational costs, a sample averaging technique was proposed. The technique demonstrated improvements, including enhanced robustness to noise and achieved an 85% recognition accuracy at a signal-to-noise ratio (SNR) of -6 dB for all 12 signals. However, achieving good accuracy required a significant number of signal samples, with 22,680 signals for training and 9,720 signals for validation.

According to [7] presented an alternative method for analyzing and identifying low probability of intercept (LPI) radar signals using the Wigner-Ville distribution (WVD). The WVD was modified with Hamming and Kaiser windows to reduce noise effects during identification. Both interpulse and intrapulse analyses were performed to estimate various signal parameters. Instantaneous power (IP) and instantaneous frequency (IF) were derived from the WVD for interpulse and intrapulse analyses, respectively. A rule-based classifier was then designed using these parameters to identify the radar signals. Performance analysis, including confusion matrices, was conducted at different signal-to-noise ratios (SNRs). The results demonstrated a 95% identification accuracy at a minimum SNR of 0 dB for the considered radar signals. However, the study focused on a specific type of frequency agile radar signal, and further research is needed to evaluate the method's performance with different types of agile radar signals.

From the work of [8] a radar signal modulation recognition algorithm based on an improved convolutional neural networks (CNN) model was presented. Since CNN model has some shortcomings in the signal modulation recognition, such as long training time and poor generalization, the dense connection block layer and the global pooling layer are added in the CNN model to improve its performance. eight types of radar signals are used to verify the feasibility of the proposed algorithm, and the results show that the algorithm based on the improved CNN has the advantages of high recognition rate, short training time and good generalization. The results shows that the algorithm based on the improved CNN has the advantages of high recognition rate, short training time and good generalization. The confusion matrix of the improved CNN in SNR =-10db and the recognition rates of different types of signals in SNR = -10 DB. However, the convolutional neural networks (CNN) model has some shortcomings in the signal modulation recognition, such as long training time and poor generalization.

From the author of [1]ResXNet was proposed, with a novel multiscale lightweight attention model, the model has a larger receptive field and a novel grouped residual structure to improve the feature representation capacity of the model. In addition, the convolution block attention module (CBAM) is utilized to effectively aggregate channel and spatial information, enabling the convolutional neural network model to extract features more effectively. The input time-frequency image size of the proposed model is increased to 600 × 600, which effectively reduces the information loss of the input data. The average recognition accuracy of the proposed model achieves 91.1% at -8 dB. It performs better in terms of unsupervised object localization with the class activation map (CAM). However, for future research, more lightweight models for radar signal recognition, as well as the use of CAM in radar signal recognition and localization need to be explored.

In work of [9] a novel network combined a shallow convolution neural network (CNN), long short-term memory (LSTM) network and deep neural network (DNN) to recognise six types of radar signals with different signal-to-noise ratio (SNR) levels from −14 to 20dB was presented. Raw signal sequences in the time domain, frequency domain and autocorrelation domain are as input for a shallow CNN. And DNNs will output the signal modulation types directly, the simulation results demonstrate that the accuracies in autocorrelation domain are all more than 90% at −6dB and close to 100% when SNR > −2dB. However, despite the novelty demonstrated by the research, high training data sets was needed and requires a high SNR of 20dB to achieve performance accuracy stability of 100%.

According to the author of [10] the usefulness of an algorithm in the scenario of LPI radar signal detection and recognition based on visibility graphs (VG) was explored. More network and feature information can be extracted in the VG two-dimensional space, this algorithm can solve the problem of signal recognition using the autocorrelation function. Signal detection simulation analysis shows that when the SNR is −10 dB, the SDP is 90.9%, and as the SNR increases, the SDP also increases, especially when SNR is greater than −8 dB, the SDP is basically 100%. However, in future research, it was expected to extend the VG theory to radar signal sorting and radar working pattern recognition applications.

In [11] novel intra-pulse modulation recognition method based on the high-order spectrums of radar signals was developed. Automatic soft thresholding is implemented in the deep residual network to adaptively eliminate redundant information in the process of feature learning and improve the learning effect of valuable features in distribution images of corresponding third-order spectrums. The extensive simulations compared with the other four methods further reveal the excellent classification performance of the proposed method. The approach achieves an overall probability of successful recognition of 93.5% for eight kinds of modulation signals, even when the SNR is just − 8 dB. Outstanding performance proves the superiority and robustness of the proposed method. However, it has recognition mistakes which mainly occurs between the signal pairs that have similar TSDIs, such as EQFM and Frank code signals, LFM and Frank code signals and the process of image resizing also makes small frequency jump blurred. The losses and blurs of this small frequency information finally leaded to confusion between signals.

From the author of [5]ResXNet was proposed, with a novel multiscale lightweight attention model, the model has a larger receptive field and a novel grouped residual structure to improve the feature representation capacity of the model. In addition, the convolution block attention module (CBAM) is utilized to effectively aggregate channel and spatial information, enabling the convolutional neural network model to extract features more effectively. The input time-frequency image size of the proposed model is increased to 600 × 600, which effectively reduces the information loss of the input data. The average recognition accuracy of the proposed model achieves 91.1% at -8 dB. It performs better in terms of unsupervised object localization with the class activation map (CAM). However, for future research, more lightweight models for radar signal recognition, as well as the use of CAM in radar signal recognition and localization, will be explored.

2. Methodology

Four radar signals based on pulse-pulse frequency agility were modeled as the objectives of this paper. These are normal radar signal (NRS), frequency hopping radar signal (FHRS), 2-frequency shift keying radar signal (2FSKRS), and a combination of frequency hopping radar signal (FHRS) and 2-frequency shift keying radar signal (2FSKRS). The algorithmic modelling of the radar signals had various inputs based on the signal of interest and two outputs, which is the signal waveform of interest and time series of the radar signal. These signals are discussed as follows

2.1. Normal radar signal (NRS)

For NRS, four input were considered: pulse width (PW), pulse repetition interval (PRI), sampling frequency (FS) and the centre frequency (F). This radar signal has only one centre frequency that remained constant throughout the duration of the PW sections. The first step in generating the radar signal involved converting the PW and PRI from continuous time in seconds into time samples, as MATLAB only recognizes time samples.This was done using the popular signal processing for sampling time [12][13]:

$$t=NT_{S,} \text{ ………… } (1) \text{ or}$$

$$t=N/F_s \text{ ………… } (2) \text{ Hence,}$$

$$N=t*F_s \text{ ………… } (3)$$

wheret represents the time duration in secs, N is the time in samples, T_s is the sampling time and F_s is the sampling frequency. Next, the listening time, which is the difference between the PW and PRI, was determined to allow for generating the radar signal. The NRS was generated based on a sinusoidal signal with a selected time frequency for the duration of the PW. The listening time was represented by zeros using a MATLAB command.Thereafter, The PW and listening time were then concatenated to form a complete radar signal for one cycle. In this research based on the reviewed literature two cycles of the radar signal were considered, and a sample delay was introduced at the beginning of the signal to emulate a real-world signal. This delay was modelled by a quarter of the listening time. Thereafter, in other to plot the signal in time, the signal samples or the length of the signal were obtained and converted into time duration to match the generated signal and time series. Hence the output of the signal is both signal and time series in seconds to match it because MATLAB only deals with samples in time not analogue time in secs. The equation of the signal with a pulse is given as follows:

$$s(t)= Asin(2\pi f_c t) \text{…………}(4)$$

where A is amplitude, f_C is the center/carrier frequency, t is the duration of the signal, in this case (of radar signal), the PW length [14]. Furthermore, it is important to point out that t was converted to sample time using equation (3).Obtained results for this radar signal mode are presented in section 3.

2.2. Frequency hopping radar signal (FHRS)

Frequency hopping radar signalis a radar signal model that shares similarities with the NRS signal model. However, FHRS has an additional input compared to NRS, resulting in five inputs, for an extra centre frequency. In FHRS, the frequency of the first pulse differs from that of the second pulse. The same methodology used for NRS signal generation is employed for FHRS. The process begins with converting time into sample time by determining the listening time. However, in FHRS, there is an additional coding line to generate the second centre frequency, which occurs in the second cycle. This means that the first pulse is associated with the first centre frequency, while the second pulse is associated with the second centre frequency. The two pulses and their respective listening times are concatenated to form a complete output signal. Similar to NRS, the time series for FHRS is obtained using the sampling frequency to match the radar signal generation. This allows for the plotting of the signal in seconds. Section 3 showcases the plot of the FHRS signal.

2.3. Frequency Shift Keyingradar signal (2FSKRS)

The 2FSKRS shares the same input and follows the same steps as the FHRSs, with a slight variation. This difference lies in the hopping mechanism occurring within each individual pulse for each centre frequency due to the presence of two frequencies. Consequently, following the generation of the sinusoidal signal, the pulse width durations within the radar signal are concatenated into a single pulse width for each pulse. As such, equation (4) is modified to cater for this change within the pulse width as follows

$$s(t)= Asin(2\pi f_n t)\text{..........}(5)$$

where f_n is the value of the hopping frequency based on n=2, for two pulse-to-pulse hopping [14]. Plots obtained from this model are presented in section 3.

2.4. Combination of FHRS and 2FSKRS

For FHRS_2FSKRS as the name implies, it is the combination of FHRS and 2FSKRS it has a kind of two different radar signal embedded together. In the case of 2FSKRS, the frequencies within a single pulse follow a sequential pattern (F1, then F2). However, for the second pulse, the frequencies are non-sequential (F2 and F1). illustrating the change in frequencies within a single pulse, thereby creating the combination of FH and 2FSK radar signal. It is important to note that the centre frequencies consist of two concatenations: (F1 and F2 within the first pulse) and (F2 and F1 within the second pulse). The signal generated within one pulse is based on the equation (4) for just the duration of the pulse width and pattern of frequency formation is based on equation (5). Section 3 shows the plot of this signal.

2.5. Frequency representation of the Radar Signals

In other to understand the signal behavior and frequency characteristics, it is essential to employ frequency representation techniques. In this study, an algorithm was developed to generate a specific part of the frequency representation, utilizing the Fast Fourier Transform (FFT) functionality available in MATLAB. As it was mentioned MATLAB has a limitation of only dealing with samples therefore when is time to graphically display the signal, there was need to convert it into frequency series in hertz (Hz). This conversion process was added to this program to get the frequency representation of the radar signals. The weights S(f) in the equation define a frequency domain representation for the deterministic signal s(t); it allows the evaluation of periodicities in the signal (the unit is the number of oscillations per second, expressed in Hz [15]. This may be obtained from s(t) by taking the Fourier transform (FT)[15]:

$$S(f) = \int_{-\infty}^{\infty} S(t)\, e^{-j2\pi f t} dt\text{..............}(6)$$

The second reason for embarking on the process of frequency conversion is to also show effect of the Hilbert transform on the signal, where real signal is converted to its analytic format.

2.6. Hilbert transform of radar signal

Hilbert transformin In the area of signal processing, is a mathematical operation that is used to analyze signals, For a signal s(t), its Hilbert transform may be expressed using the FT F {·} of s(t) as [16]:

$$H\{s(t)\} = F_{t\leftarrow f}^{-1}\{(-j\ sgn\ f)F_{t\leftarrow f}\{s(t)\}\}\text{...........}(7)$$

As such;

$$H\{\cos(2\pi f_o t)\} = \sin(2\pi f_o t)\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

$$H\{\sin(2\pi f_o t)\} = -\cos(2\pi f_o t)\ldots\ldots\ldots\ldots\ldots(9)$$

The focus of interest in this work was the analytic form of the Hilbert transform that was utilized to get clear of the unwanted negative frequencies produced by the Fourier transform. It offers two key benefits;

• Reduces the overall bandwidth by half, permitting sampling at half the Nyquist rate without aliasing

• Avoidance of interference terms caused by the interaction of positive and negative components in quadratic time-frequency distributions (TFD) .

The mathematical representation of the analytic version of a signal based on Hilbert transform is given by [16];

$$Z(t) = S(t) + i\, H\{S(t)\} \ldots\ldots\ldots(10)$$

Hence the analytic version is formed the real version of the signal plus the complex version of its Hilbert transform.

3. Results and discussion

MATLAB simulation was performed in other to determine the performance of the model of the radar signal waveforms. The simulation and hence result contain three parts. Firstly, the frequency agile radar signals model considered are NRS, FHRS, 2FSKRS and combination of FHRS and 2FSKRS. Secondly, obtaining the analytic version of the waveforms through Hilbert transform. Lastly, obtaining their frequency representations using Fast Fourier transform of both the real and analytic versions. The results obtained are presented as follows

3.1. Normal Radar Signal (NRS)

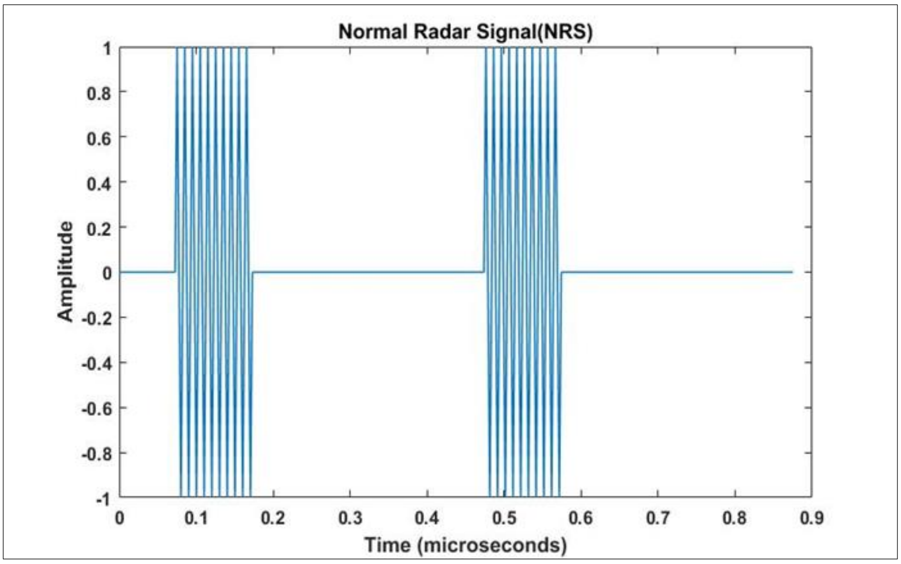


Figure 1a Time representation of Normal Signal Radar

Figure 1a shows the plot of NRS generated with each pulse having the same center frequency, specifically 10MHz throughout the pulse width of 1 µs. It also shows the constant frequency during the pulse width as similar sinusoid is observed in both pulses. Figure 1b. shows the frequency representation and conversion of the signal using fastFourier transform (FFT). The LHS of Figure 1b shows the normal FFT representation, where it is observed that frequency is present at the original 10 MHz and a mirror at 30 MHz. However, the RHS shows the elimination of the mirrored frequency based on frequency representation of the analytic version of this signal gotten through the Hilbert transform

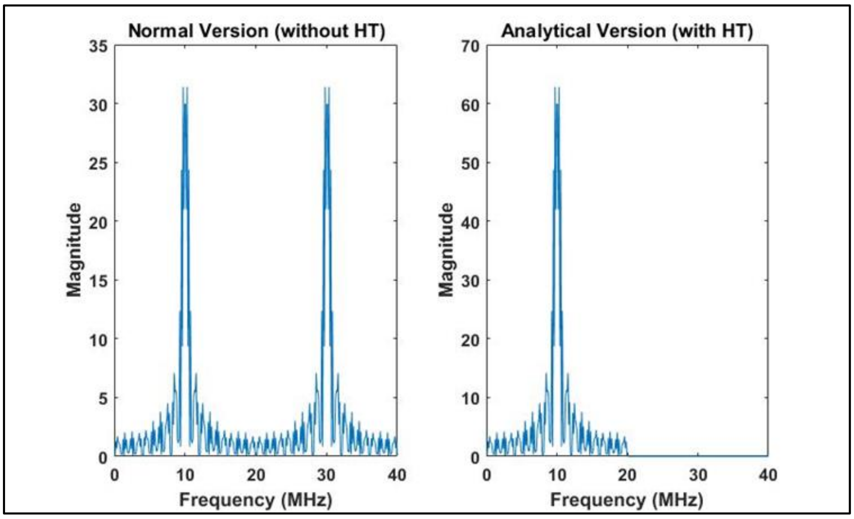


Figure 1b Frequency representation of NRS

3.2. Frequency Hopping Radar Signal (FHRS)

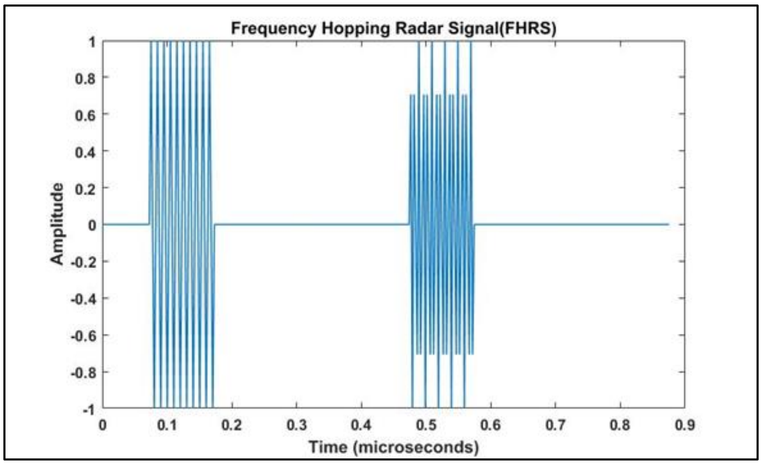


Figure 2a Time representation of Frequency Hopping Radar Signal

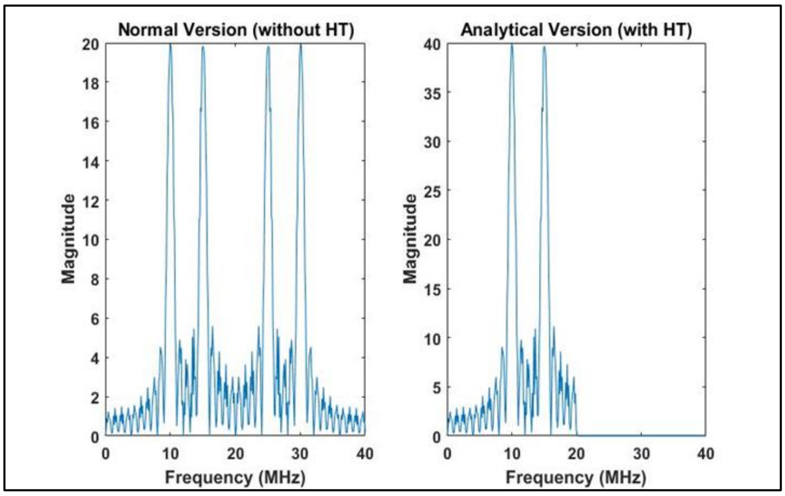


Figure 2b Frequency representation of Frequency Hopping Radar Signal

Figure 2a shows the plot of FHRS generated which the first pulse has center frequency of 10MHz, and the second pulse has center frequency of 15MHz throughout the pulse width of 1 µs.Figure 2b. shows the frequency representation and conversion of signal using fastFourier transform (FFT). The LHS of Figure 2b shows the normal FFT representation, it's observed that frequencies of 10 MHz and 15 MHz are present as the original frequencies and while the mirrored once are at 25 MHz and 30 MHz. However, the RHS shows the eliminated version of the mirrored frequency based on frequency representation of the analytic form of this signal that was gotten through the Hilbert transformation.

3.3. Frequency Shift Keyingradar signal (2FSKRS)

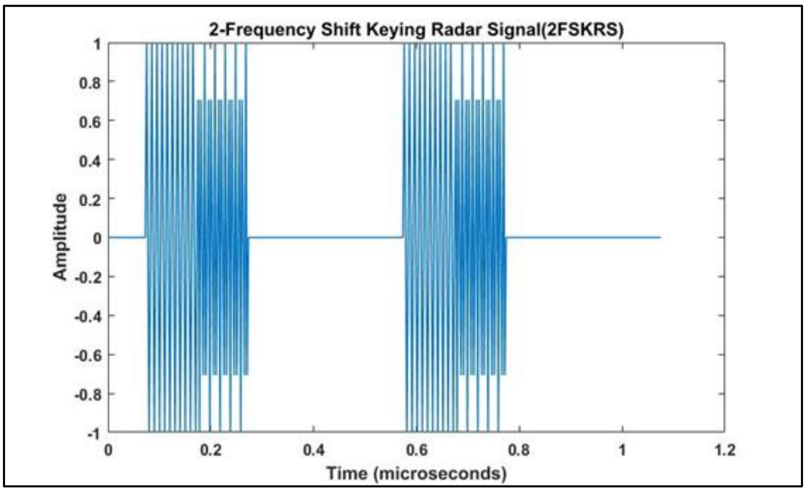


Figure 3a Time representation of2-frequency shift keying radar signal

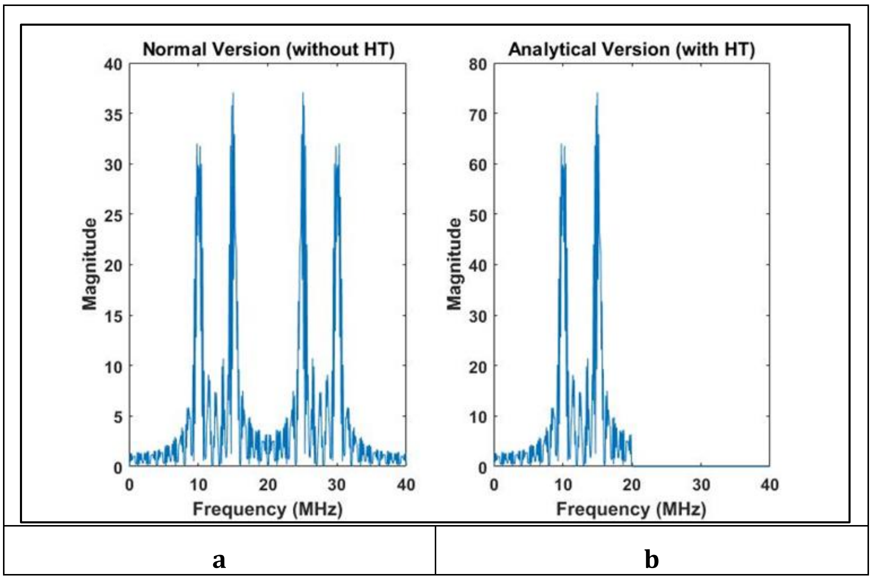


Figure 3b Frequency representation of 2-frequency shift keying radar signal

Figure 3a shows the plot of 2FSKRS generated which the first pulse has two different center frequencies 10MHz for the first half section of the first pulse and 15MHz for its second half for the pulse width duration of 1 µs. This is repeated for the second pulse in line with its design profile. Figure 3b. shows the frequency representation and conversion of signal using fastFourier transform (FFT).The LHS of Figure 3b shows the normal FFT representation, it's observed that frequencies of 10 MHz and 15 MHz are present as the original frequencies and while the mirrored once are at 25 MHz and 30 MHz. However, the RHS shows the analytic version of signal were non-required negative frequencies or mirrored frequency generated by fast Fourier transform are eliminated by the used of the Hilbert transform.

3.4. Combination of FHRS and 2FSKRS

Figure 4a shows the plot of FHRS and 2FSKRS generated which the first pulse has two different center frequencies 10MHz from the beginning of the pulse and 15MHz at the end of the pulse, but for this case of this radar signal hopping occurs at the second pulse where 15MHz start at the beginning and 10 MHz at the end of this pulse width for the duration of 1 µs. Figure 3b. shows the frequency representation and conversion of signal using fastFourier transform (FFT).The LHS of Figure 3b shows the normal FFT representation, and it's observed that frequencies of 10MHz and 15MHz are present as the original frequencies and while the mirrored once are at 25MHz and 30MHz. However, the RHS shows the Analytic version of signal were non-required negative frequencies or mirrored frequency generated by fast Fourier transform are eliminated by the used of the Hilbert transform.

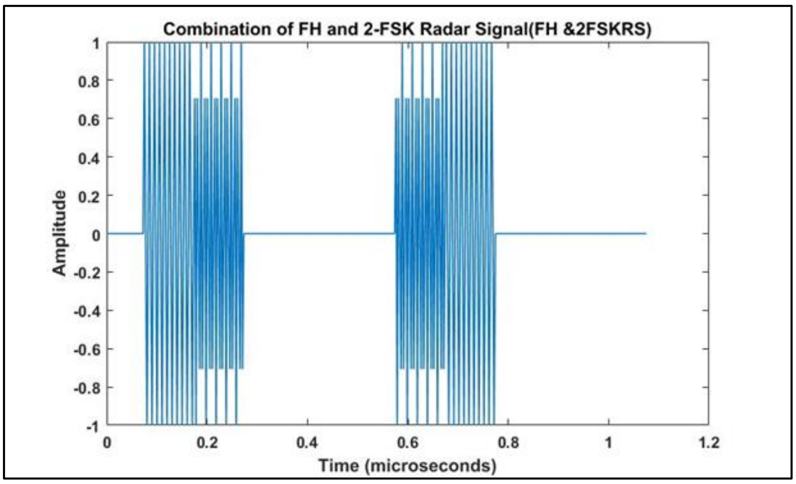
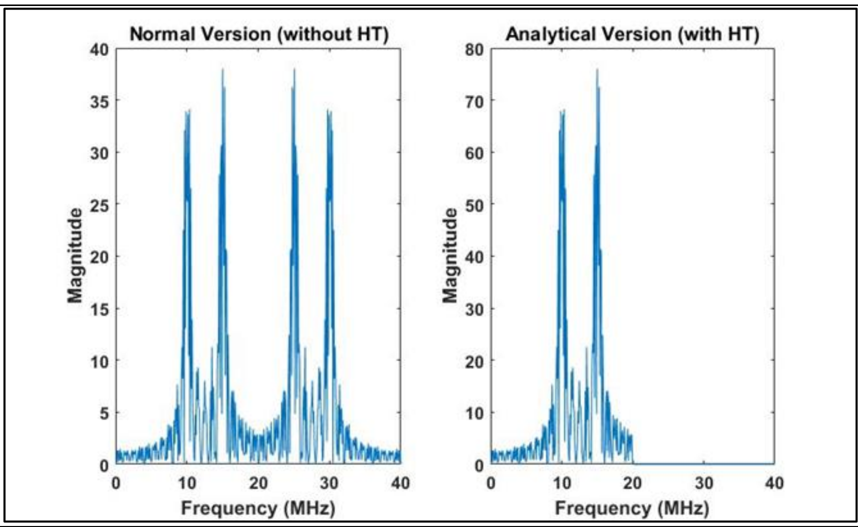


Figure 4a Time representation of combined frequency hopping & 2-frequency shift keying radar signal



a	b

Figure 4b Frequency representation of combination frequency hopping radar signal & 2-frequency shift keying radar signal

On a final note of discussion, it seen that Figures. 2b, 3b and 4b have similar frequency representations of both their real signals and their analytic versions, with slight difference of sidelobes due to crosstalk of frequencies within the pulse width. However, this is not the case in their counterpart Figures 2a, 3a and 4a involving their time representations. As such, the need for robust signal processing technique such as the time-frequency distribution is justified where it is possible to capture frequency changes at instants of time which will allow for clear distinctions between the different frequency agile radar signals.

4. Conclusion

The paper presented profile design of radar signals based on pulse-to-pulse frequency agility of four kinds of radar signals which include NRS, FHRS, 2FSKRS and combination of FHRS and 2FSKRS. Fast Fourier transform was used for the frequency representations and conversion process. However, the fast Fourier transform generated a mirrored frequencies which looks like the real signal but at different frequencies. Lastly the Hilbert transform for all kind radar signal was considered which helped in eliminating the mirrored signal that was cause by the fast Fourier transform.

Compliance with ethical standards

Disclosure of conflict of interest

We hereby declared there is no conflict of interest.

References

[1] W. Si, J. Luo, and Z. Deng, 'Radar Signal Recognition and Localization Based on Multiscale Lightweight Attention Model', J. Sensors, vol. 2022, 2022.

[2] R. Wiley, ELINT: The interception and analysis of radar signals. Artech, 2006.

[3] Adamy, ew-102-a-second-course-in-electronic-warfare'. pp. 12–16, 2004.

[4] Q. Shi, T. Zhang, X. Yu, X. Liu, and I. Lee, 'Waveform designs for joint radar-communication systems with OQAM-OFDM', Signal Processing, vol. 195, p. 108462, 2022.

[5] P. Vouras et al., An overview of advances in signal processing techniques for classical and quantum wideband synthetic apertures', arXivPrepr. arXiv2205.05602, 2022.

[6] S.-H. Kong, M. Kim, L. M. Hoang, and E. Kim, 'Automatic LPI radar waveform recognition using CNN', Ieee Access, vol. 6, pp. 4207–4219, 2018.

[7] A. A. Ahmad, M. Ajiya, Z. Y. Yusuf, and A. E. Airoboman, 'On the identification of low probability of intercept radar signals using time-frequency signal analysis and processing', J. Electr. Electron. Eng., vol. 12, no. 2, pp. 5–10, 2019.

[8] J. Cai, C. Li, and H. Zhang, 'Modulation recognition of radar signal based on an improved CNN model', in 2019 IEEE 7th International Conference on Computer Science and Network Technology (ICCSNT), 2019, pp. 293–297.

[9] S. Wei, Q. Qu, H. Su, M. Wang, J. Shi, and X. Hao, 'Intra-pulse modulation radar signal recognition based on CLDN network', IET Radar, Sonar \&Navig., vol. 14, no. 6, pp. 803–810, 2020.

[10] W. A. N. Tao, J. Kaili, L. Jingyi, T. Yanli, and T. Bin, 'Detection and recognition of LPI radar signals using visibility graphs', J. Syst. Eng. Electron., vol. 31, no. 6, pp. 1186–1192, 2020.

[11] K. Chen, L. Zhu, S. Chen, S. Zhang, and H. Zhao, 'Deep residual learning in modulation recognition of radar signals using higher-order spectral distribution', Measurement, vol. 185, p. 109945, 2021.

[12] V. K. Madisetti, The Digital Signal Processing Handbook-3 Volume Set. CRC press, 2018.

[13] J. G. Proakis, Digital communications. McGraw-Hill, Higher Education, 2008.

[14] T. A. O. Chen, L. Liu, and X. Huang, 'LPI Radar Waveform Recognition Based on Multi-Branch MWC Compressed Sampling Receiver', IEEE Access, vol. 6, pp. 30342–30354, 2018, doi: 10.1109/ACCESS.2018.2845102.

[15] B. Boashash, Time-frequency signal analysis and processing: a comprehensive reference. Academic press, 2015.

[16] A. Derviskadic, G. Frigo, and M. Paolone, 'Beyond Phasors: Modeling of Power System Signals Using the Hilbert Transform', IEEE Trans. Power Syst., vol. 35, no. 4, pp. 2971–2980, 2020, doi: 10.1109/TPWRS.2019.2958487.