Classification of Airborne Radar Signals based on Time-Frequency Features using Wigner-Ville Distribution

AHMAD Ashraf A.[1,2], AJIYA Mohammed[2], YUNUSA Zainab[2], HUSSAINI Habibu[3], ADEMOH Isah A.[3]

[1] Nigerian Defence Academy (NDA), Nigeria,
Department of Electrical/ Electronic Engineering, Faculty of Engineering and Technology,
Kaduna, Nigeria, aaashraf@nda.edu.ng

[2]Bayero University Kano (BUK), Nigeria,
Department of Electrical Engineering, Faculty of Engineering and Technology,
Kano, Nigeria

[3]Federal University of Technology (FUT), Nigeria,
Department of Electrical and Electronics Engineering, School of Electrical and Electronics Engineering,
Minna, Nigeria

Abstract ***– This paper presents a classification system for airborne radar signals using Wigner-Ville distribution (WVD) and rule-based classifier for use in the field of electronic warfare (EW) for electronic intelligence gathering. The signals considered in this paper are mostly of multi-group low probability of intercept (LPI) capabilities of phase and frequency modulation origin. The WVD used in this paper was altered using two window functions in the time-lag domain in order to counteract the shortcomings of the normal WVD. The classifier was based on time, frequency and phase analyses carried out in order to estimate important features for the classifier rules. Performance analysis was carried out in order to determine classification accuracy. Results obtained showed a classification accuracy of 100% at signal-to-noise ratio (SNR) equal to or greater than 1 dB. Computational complexity analysis of the methodology used showed a highest order of three, similar to previous related paper.***

Keywords: ***electronic warfare (EW), low probability of intercept (LPI), rule-based classifier, signal-to-noise ratio (SNR),Wigner-Ville distribution (WVD).***

I. INTRODUCTION

Electronic warfare support (ES) is the division of electronic warfare (EW) involving actions that include searching for, intercepting, identifying, locating and localizing sources of intentional and unintentional radiated electromagnetic energy for the purpose of immediate threat recognition, targeting, planning, and conduct of future operations [1]. A key aspect of ES is the signal analysis and classification of radar signals. These radar signals in the field of EW are normally of low probability of intercept (LPI) characteristics and as such the intercept receiver needs advanced signal processing tools for proper identification [2]. LPI waveform recognition techniques (LWRT) form this identification process; usually done through classification based on features extracted from analyses carried out [3].

Within the last decade, LWRT researchers have been proposing and presenting new classification methods using signal processing tools for better performance analysis. This performance analysis is presented through improved signal-to-noise ratio (SNR) and computational complexity among others. Another aspect of the LWRT researches is the scope of test signal; some have focus on non-LPI modulations only while most times LPI signals are considered due to their unique characteristics. These LPI researches may focus on the phase modulation based ones or frequency modulation based ones or both frequency and phase modulation as considered in this paper and the preceding literatures. One of the key research on multi-group test radar signals used Wigner and Choi–Williams time-frequency distributions (WD and CWD) for automatically recognizing eight radar waveforms of pulse compression modulation using a supervised classification system [4]. Simulation results obtained showed correct classification rate of 98% at signal-to-noise ratio (SNR) of 6 dB. However, the classification method presented depended on estimation accuracy of the carrier frequency. More recently, parameter estimation based approach for estimating a hybrid low probability of intercept (LPI)-based radar signal of frequency shift keying (FSK) and phase shifting keying (PSK) components was presented [5]. The presented algorithm has higher accuracy of parameter estimation when the signal-to-noise ratio (SNR) is above 11 dB. The method proposed had the advantage of simplicity as the fast Fourier transform is the main analysis tool, however, only a single LPI signal of hybrid nature was considered.

A radar type classification system of various expansions and practical scenarios consideration using spectrogram and other signal processing tools was presented [6]. Results obtained showed 100% classification accuracy at SNR of 11dB. However, signal parameter estimation was not carried out. A recognition method for the LPI-radar signals of different group using time-frequency analysis was proposed [7]. The method combined the oldest form of the time-frequency distribution (TFD), the short-time Fourier transform (STFT) with the convolutional neural network (CNN) as the classifier. Obtained results showed a good classification accuracy of 90% at minimum SNR of -5dB. However, polyphase coded LPI signals were not considered in this paper. Most recently, radar waveform recognition system was presented for eight different signals using time-frequency analysis and classification system [8]. Time-frequency analysis involves the WVD and the Choi-Williams distribution (CWD) while the classifier is the support vector machine (SVM), optimized by artificial bee colony (ABC) algorithm. Simulation results indicated that the overall recognition rate is 92% when SNR is −4 dB even though some individual signal may require higher SNR at 100%. Despite achieving a good result, the major drawback of this research is associated with high computational complexity due to the classifier used.

In view of these literatures, this paper focused on estimation of frequency or phase parameters of LPI (CW) signals for the purpose of classification using a rule-based classifier. Secondly, the WVD was developed as the main TFD and altered with emphasis on achieving a low computationally complex quadratic time-frequency distribution (QTFD). Further processing on the WVD such as instantaneous power and frequency approximation was carried out in order to extract the required features for classification. Section II presents the methodology used based on various time-frequency analyses carried out; section II presents simulation set-up and performance analysis and conclusion are given at the end of the paper.

II. TIME-FREQUENCY ANALYSIS

Joint time-frequency analysis is an evolution of mathematical ideas and concepts used in the analysis of time-varying spectra of signals in order to cater for various problems in numerous fields [9]. This joint analysis is used to overcome the limitations of analysis in solitary time domain or frequency domain. Recently, the applications of this type of joint analysis in psychological testing was examined [10].The WVD is a key member of Cohen's class of TFD, developed to counteract the limitations of linear TFDs through better distribution of signal energy over a joint-time frequency domain. Other TFDs include Spectrogram, Wavelet transform, Gabor Transform, S-Transform among many others [11]. The WVD is mathematically expressed as shown in (1).

$$W_z(t,f) = \int_{-\infty}^{\infty} z\left(t+\frac{\tau}{2}\right) z^*\left(t-\frac{\tau}{2}\right) e^{-j2\pi f\tau} d\tau \quad (1)$$

where $\mathrm{z(t)}$ is the analytical or the complex form associate of the signal $\mathrm{s(t)}$, and * denotes the complex conjugate of the signal of interest. However, WVD suffers the major drawbacks of non-negative energy distribution, inner terms and cross-terms production which often lead to mistranslation and lack of clarity of the information represented [12]. As such, this paper uses an altered version of WVD with the aid of two separable kernel filters to counteract these drawbacks. The altered version of the WVD used in this paper is given in (2).

$$\mathrm{W_{z,alt}(t,f)} = \int_{-\infty}^{\infty} \mathrm{g_2(\tau) g_1(t)} * \mathrm{z}\left(\mathrm{t}+\frac{\tau}{2}\right) \mathrm{z}^*\left(\mathrm{t}-\frac{\tau}{2}\right) \mathrm{e}^{-\mathrm{j}2\pi\mathrm{f}\tau} \mathrm{d}\tau \quad (2)$$

Equation (2) shows the altered WVD is simply a result of a lag dependent window ($\mathrm{g_2(\tau)}$), and a smoothing window in time ($\mathrm{g_1(t)}$) in the time-lag domain. The Hamming window is used as the time-lag kernel, while the Kaiser window is used as the time-smoothing kernel due to their various advantages enumerated in [13]. In order to obtain the features for classification of the radar signals, two main analyses were carried out. The first analysis involved determining the time-parameters (pulse width (PW) and pulse repetition period (PRP)) in order to distinguish between LPI and non-LPI. The time marginal instantaneous power (IP) was used in this analysis and is obtained through integral of the WVD with respect to frequency due to ease of implementation and low computational complexity [14]. This IP is mathematically given in (3) and (4).

$$\mathrm{IP(t)} = \int_{-\infty}^{\infty} \mathrm{W_{z,alt}(t,f)\, df} \quad (3)$$

$$\mathrm{IP(t)} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \mathrm{g_2(\tau) g_1(t)} * \mathrm{z}\left(\mathrm{t}+\frac{\tau}{2}\right) \mathrm{z}^*\left(\mathrm{t}-\frac{\tau}{2}\right) \mathrm{e}^{-\mathrm{j}2\pi\mathrm{f}\tau} \mathrm{d}\tau\, \mathrm{df} \quad (4)$$

The IP was further smoothed by careful selection of normalized hamming window in order to reduce noise during the parameter estimation. Thereafter PW and PRP is obtained using a straightforward algorithm to measure the signal time at 'high' and 'low' level respectively at the medium chosen threshold of 37.5%. This chosen threshold is based on paper test signals belonging to non-LPI and LPI signals normally measured at half and quarter percentile thresholds respectively [2, 15].

The second analysis involved determining the phase and frequency parameters of the LPI radar signals. The main tool selected for this analysis was the instantaneous frequency (IF). The IF was gotten from the altered WVD [12] and is mathematically given in (5) [16].

$$\mathrm{IF(t)} = \max_{f}\left(\mathrm{W_{z,alt}(t,f)}\right) \quad (5)$$

Equation (5) shows the IF is gotten from the peak ranges location of the altered WVD time-frequency representation (TFR) along the frequency axis (and hence the *f* associated the max. The second analysis was divided into two sections with accompanying designed algorithm based on the preceding explanation. The first section involved grouping of the LPI radar signal into LPI-phase or LPI-frequency. The second section involved obtaining the frequency or phase parameter of the radar signal based on the grouping carried out in the first section.

Bandwidth (BW) was identified as the main feature for the first section grouping based on radar signals' IF. It was observed that for the phase modulation based LPI signal, the frequency is mostly constant (except during the phase changes) while the opposite is the case for frequency modulation LPI signal. The BW for this section is defined in (6).

$$\mathrm{BW} = \mathrm{f_e} - \mathrm{f_s} \quad (6)$$

where $\mathrm{f_e}$ is the frequency at the end of the pulse while $\mathrm{f_s}$ is the frequency at the start of the pulse. For LPI-phase signals, BW is approximately zero due to its constant frequency modulation while For LPI-frequency signals; the BW will be greater than zero as the characteristics of these signals indicates a varying frequency modulation. The second section of this analysis involved the sub-analysis of the LPI radar signals. For the LPI –phase radar signals, it involved determining the sub-time of the phase changes (peaks and dips) and hence the number of changes; while for the LPI-frequency; it involves determining the frequency parameter of the signal based on how high the BW is. Costas coded FSK normally has low BW due to presence of seven different frequencies and difference between them can never be high as observed from the literature while Linear FM radar signal has high BW due to its chirp nature hence concluding all analyses required for classification. The rule-based classifier was chosen in this paper due to its simplicity and is formed from the if-else syntax. The rules formation for the classifier is given in Fig. 1.

It can be seen from Fig. 1 that there are eight rules considered for the rule based classifier used in this paper. Five of them are associated with five test radar signals of different group while the remaining three are associated with an unknown signal. The unknown signal classification is based on non-radar signal that may be intercepted by the classifier. PW threshold of 1.5μs is used to separate the LPI from the non-LPI signals based on examples given in key references related to this paper [15] and researched carried out in [17, 18]. The BW of 0.5MHz is used as a limit threshold to separate simple pulsed radar signal from a possible unknown signal when the PW is small or separate LPI signal of phase modulation origin from that of frequency modulation origin when the PW is bigger.

The number of phase changes determines the actual identity of the LPI – phase signal. Examining the literature of Barker codes for the LPI signal based, it is seen that BPSK radar signal normally has phase changes

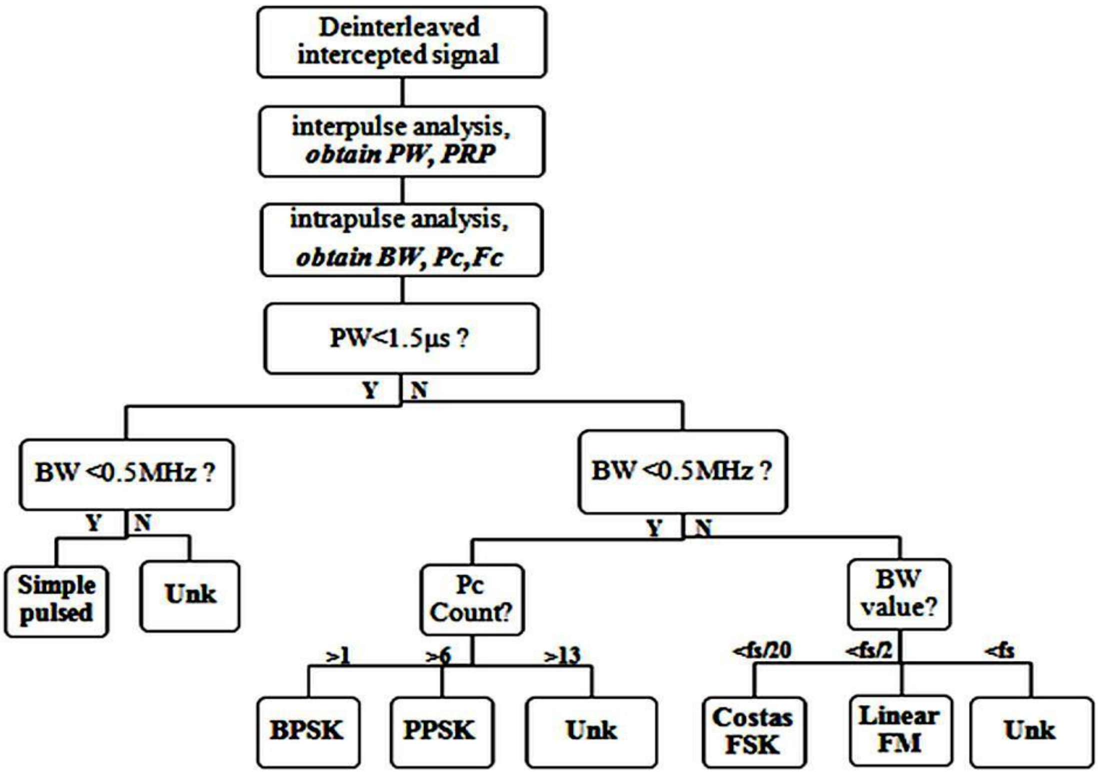

Fig. 1 - Schematic diagram for the rule-based classifier of the paper [definition of terms: Pc – phase changes, Fc- frequency changes, fs-sampling frequency, Unk - unknown//non-radar signal]

less than six while that of PPSK is from six but not greater than thirteen [19]. As such the rule for an unknown signal is created for signal with high PW, low BW but with very high number of phase changes (greater than 13). As for the LPI-frequency radar signals, it seen that the BW value as associated with sampling frequency determines actual identity based on previous analysis.

The FSK radar signal based on Costas codes normally has a small BW usually between 1-2MHz and as such the limit of 20th division of sampling frequency is used. The BW for linear FM radar signal is higher and can run from10th division of sampling frequency to the maximum value of sampling frequency of half the sampling frequency [19]. The lower limit of the linear FM radar signal is based on literature presented while that of the higher limit is based on the Nyquist sampling theorem. Finally the last branch/rule for an unknown signal is defined for a signal which can be noise that doesn't follow this theorem.

III. RESULTS AND DISCUSSION

In order to test the accuracy of the radar signal classifier system designed, Monte Carlo simulation is carried out in the presence of noise to determine the relationship between the classification accuracy and range of SNR in line with convention. The Monte Carlo simulation is used in this paper to model practical airborne radar environment of various sources of interferences for classification of the airborne radar signals.

The classification accuracy used in this paper is represented by the probability of correct classification (PCC) with unit of percentage based on when correct classification is obtained. The noise is modeled by additive white Gaussian noise (AWGN) of Gaussian probability density function models the random nature of the various type of noise associated with the practical radar scenario. A total of five radar test signals are considered for this simulation, each belonging to one group and characteristics of each signal are adopted from Table 1 of [14]. The PRP of all the signals was kept at constant value of 100 µs of medium category based on the table presented in [20]. Sampling frequency of 40MHz is used based on current practical radar surveillance technology [6]. PW and frequency selection is based on the signal characteristics and modeled around the sampling frequency with full details in [2, 15, 19]. PCC is the ratio of number of correct classification to total number of classification which is chosen as ten (10) in this paper while SNR is ratio of the signal power to noise power obtained through variance. PCC is expressed in percentage while SNR is expressed in dB; the result obtained for this classification is given in Fig. 2.

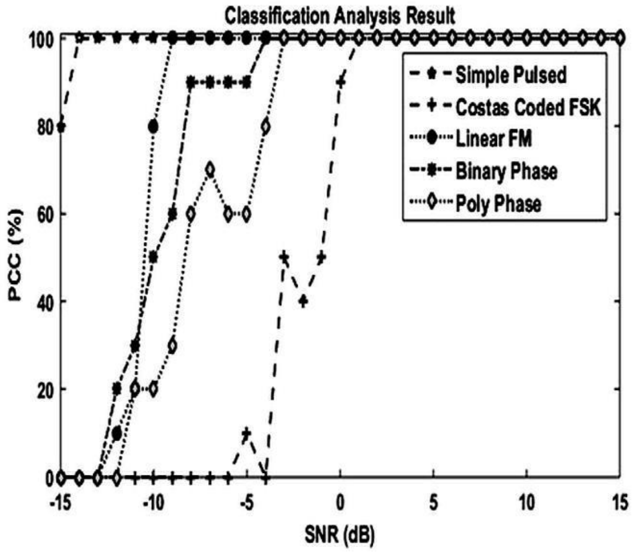

Fig. 2 - Classification accuracy results of airborne radar signals

It is seen from the Monte Carlo simulation results of Fig. 2 that the relationship between internal modulation complexities and main tool of analysis plays the most important role in the PCC of the intercepted radar signal. As such the best result is obtained by the simple pulsed radar signal of constant frequency modulation with 100% PCC at very low SNR of -14dB. It takes a difference of 5dB for the next signal of linear FM radar signal to achieve similar feat of 100% PCC at SNR of -9dB. The chirp nature of this signal with characteristics of increasing linearly gives this type of signal a very good classification result. Moreover, the main intention of the original WVD design is to concentrate the signal along its instantaneous frequencies and the linear FM has a linear form of instantaneous frequencies. LPI-phase signals achieves 100% PCC at very similar SNR of -4dB and -3dB for BPSK and PPSK signal respectively. Both signal shares the same frequency characteristics of constant frequency modulation except during the phase changes. As such, the BPSK performs slightly better due to having smaller phase changes than PPSK radar signal. The Costas FSK achieves 100% PCC at positive SNR of 1dB. This is because for correct classification of this FSK radar signal, not only is the correct estimation of its seven different frequencies required, but also, their positioning based on Costas arrangement must also be estimated correctly. As such it can easily be misclassified as any other signal or an unknown signal. The SNR of 1dB signifies the minimum SNR required by this paper to achieve a classification accuracy of 100% irrespective of the incoming signal. At SNR of 0dB where signal power is the same as noise power, classification accuracy of 90% can be guaranteed by the airborne radar classifier in this paper.

The computational complexity (CC) is a common form of performance indicators for estimation or classification system. In fact, most of the previous related papers of high estimation and classification robust designs explores the computational complexity of the designs in different forms [6, 21]. The CC based on instruction cycles is necessary when there is need to implement this radar system design on an embedded system. It is also needed when there is need to access the practicality of implementing this design for signal analysis and classification applications. The actual speed of the implementation would depend on that of the instruction cycle. The CC of this design is divided into three sections; the altered WVD as the main tool of analysis, IP for interpulse analysis and IF for intrapulse analysis and are given in (7) – (9) respectively.

$$\mathrm{CC_{altered\ WVD}} = \mathrm{N_tN + N_dN + N_lN + N_t log_2(N_t)N} \tag{7}$$

$$\mathrm{CC_{IP}} = \mathrm{N_tN} \tag{8}$$

$$\mathrm{CC_{IF}} = \mathrm{N_tN_p} \tag{9}$$

where $\mathrm{N_t}$ is the window length; N is the signal length, $\mathrm{N_d}$ is the Doppler-independent (DI) kernel length, $\mathrm{N_l}$ is the lag-independent (LI) kernel length and $\mathrm{N_p}$ is the pulse width length. All these parameters are fixed except for pulse width as it depends on the signal in consideration. Equation (7) shows the CC for the altered WVD being a summation of four different processes which corresponds to getting the instantaneous autocorrelation function (IAF), windowing the IAF, smoothing the IAF and getting the altered WVD from the altered IAF using Fourier transform. The total CC for whole radar classifier system design would therefore combine the (7) - (9) and is presented in (10).

$$\mathrm{CC_{total}} = \mathrm{N\ (2N_t + N_d + N_l + N_t log_2 N_t) + N_tN_p} \tag{10}$$

There are five terms in (10) mostly of second order with a single third order and therefore the CC can be given approximately in (11).

$$\mathrm{CC_{total}} \cong \mathrm{N(N_t log_2 N_t)} \tag{11}$$

Equation (11) takes into cognizance of the highest order of three due to Fourier transform during the altered WVD obtainment. For comparison purpose of CC based on instruction cycles, CC results obtained in a similar paper [6] is approximated CC in (12).

$$\mathrm{CC_{total}} \cong \mathrm{N_p(N_{w2} log_2 N_{w2})} \tag{12}$$

Therefore it can be accurately said that CC obtained in this paper is similar to that of methodology used in [6]. It is important to state that no proposed method is exactly the same and similarity considered for comparison analysis is based on some form of radar signal analysis carried out. The comparison analysis presented for methodologies that focused on at least one sub-group each of either LPI-frequency or LPI-group is given in Table 1.

TABLE 1: Comparison Analysis for LPI-multi groups at 100% classification accuracy

S/N	Main Signal Processing tool	LPI-phase	LPI-freq
1	WD, CWD [4]	9dB	6dB
2	Multi-phase difference [5]	11dB	11dB
3	Spectrogram [6]	5dB	9dB
4	STFT [7]	-3dB	-2dB
5	CWD [3]	-4dB	-8dB
6	WVD (*altered*)	-3dB	1dB

It is important to point out that some of the papers presented in Table 1 also considered the non-LPI signal for the sake of completion just like this paper. Also the classification accuracy of 100% at the stated SNR presented in Table 1 is based on similar test radar signals as the one considered in this paper and not on other possible different signals of similar group. Most importantly, the quoted SNR showed in Table 2 shows the worst case scenario SNR for the 100% classification accuracy which includes all sub members for the LPI test signals. This is because that is the SNR for which excellent classification is guaranteed for practical implementation. Furthermore, it was observed that this worst case scenario is normally the result obtained for the poly-phase LPI in the LPI-phase signals group and the one obtained for FSK in LPI-frequency groups due to their more complicated internal modulations when compared to the other members of the same group. Four main points are deduced from Table 2 among other points for the purpose of comparisons. Firstly, it is seen for the LPI-phase signals, that the method used in this paper outperforms most of the previous papers except for a single case. This case is CWD method of [3] where slight superiority is noticed at SNR difference of 1dB. However, this method uses larger number of samples in training and validation for the classifier used. Secondly, for the LPI-frequency radar signals group, two other papers outperforms this paper with SNR difference of 3dB observed for [7] and 9dB for [3]. These superior cases are observed to be more recent and have much superior classifiers. However, this paper edges them when computational complexity is considered due to using less number of features for classification.

Thirdly, when the all the LPI signals are considered from comparison analysis in Table 2; it is seen that it is not always clear which of the LPI-group is easier to classify due to variations. This can be attributed to the test signals having slight different parameter values such as FSK signal of different number of internal frequencies among other examples. Furthermore, the method chosen combined with the classifier used is also a reason of these variations. Finally, it is seen that the method used in this paper falls in-line with recent papers as clear classification accuracy improvement is noticed when compared to older previous related researches.

IV. CONCLUSIONS

The proposed method for classification of airborne radar signals of mostly LPI properties was explained in this paper. The main signal processing tool of analysis was the WVD aided by IP and IF approximated from it. Classifier is of the if-else construct from the parameters obtained from two main analyses. Results obtained showed perfect classification accuracy for any signal considered from minimum SNR of 1dB. CC based on instruction cycles is similar to that of previous paper where similar CC was carried presence 5 terms averagely and 3rd order as highest term. Finally it is also evident that proposed method outperformed previous papers except for most recent methods that utilized robust classifier of higher CC. Further work would involve expanding the test radar signals to accommodate other theoretical radar designs and used of other QTFDs in order to examine their radar signals classification competency.

REFERENCES

[1] F. Neri, "*Introduction to Electronic Defense Systems*", North Carolina: SciTech Publishing, 2006.

[2] P. E. Pace, "*Detecting and Classifying Low Probability of Intercept Radar*", Massachusetts: Artech House, 2009.

[3] 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.

[4] J. Lunden and V. Koivunen, "*Automatic Radar Waveform Recognition*" IEEE Journal of Selected Topics in Signal Processing, vol. 1, pp. 124-136, 2007.

[5] H. Xiong, D.-G. Zeng, X.-D. He, and B. Tang, "*Parameter Estimation Approach of FSK/PSK Radar Signal*" Journal of Electronic Science and Technology, vol. 8, pp. 341-345, 2010.

[6] A. A. Ahmad and A. Z. Sha'ameri, "*Classification of Airborne Radar Signals based on Pulse Feature Estimation using Time-Frequency Analysis*" Defence S&T Technical Bulletin, vol. 8, pp. 103-120, 2015.

[7] X. Wang, G. Huang, Z. Zhou, and J. Gao, "*Radar Emitter Recognition based on the Short Time Fourier Transform and Convolutional Neural Networks*", in 2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), pp. 1-5, 2017.

[8] L. Liu, S. Wang, and Z. Zhao, "*Radar Waveform Recognition Based on Time-Frequency Analysis and Artificial Bee Colony-Support Vector Machine*", Electronics, vol. 7, p. 59, 2018.

[9] A. A. Ahmad, A. M. Lawan, M. Ajiya, and Z. Y. Yusuf, "*Sorting of Low Probability of Intercept Radar Signals Based on Frequency Modulation Constancy Using Wigner-Ville Distribution*", in *2019 I*EEE Asia-Pacific Conference on Applied Electromagnetics *(APACE)*, pp. 1-5, 2019.

[10] R. Romulus and G. Cornelia, "*Time-frequency Representations Application in Psychological Testing*", Journal of Electrical & Electronics Engineering, vol. 8, pp. 39-42, 2015.

[11] A. Saliu, A. Ahmad, A. Tekanyi, O. Eguaroje, and J. Ayeni, "*Pulse-To-Pulse Time-Frequency Analysis of an Agile Pulsed Radar Signal Using the Spectrogram Distribution*", *ATBU* Journal of Science, Technology and Education, vol. 6, pp. 206-216, 2018.

[12] B. Boashash, "*Time-Frequency Signal Analysis and Processing: A Comprehensive Reference"*, 2nd ed. London: Academic Press, 2016.

[13] K. Prabhu, *Window "Functions and Their Applications in Signal Processing"*. Florida: CRC press, 2013.

[14] A. A. Ahmad, M. Ajiya, Y. Z. Yusuf, and A. E. Airoboman, "*On The Identification of Low Probability of Intercept Radar Signals using Time-Frequency Signal Analysis and Processing*", *Journal of Electrical and Electronics Engineering,* vol. 12, pp. 5-10, 2019.

[15] R. G. Wiley, *ELINT: "The Interception and Analysis of Radar Signals*." Massachusetts: Artech House, 2006.

[16] R. Romulus and M. Lucian, "*IF Estimation Using Spectrogram and Scalogram*", Journal of Electrical & Electronics Engineering, vol. 6, pp. 25-28, 2013.

[17] A. A. Ahmad, M. Ajiya, L. M. Bello, and Z. Y. Yusuf, "*Comparison of Various Instantaneous Power Methods for the Estimation of Time-Parameters of Poly Phase Coded Radar Signal*", in 2019 2nd International Conference of the IEEE Nigeria Computer Chapter (NigeriaComputConf), pp. 1-6, 2019.

[18] A. A. Ahmad, S. Lawan, M. Ajiya, Z. Y. Yusuf, and L. M. Bello, "*Extraction of the Pulse Width and Pulse Repetition Period of Linear FM Radar Signal using Time-Frequency Analysis*", Journal of Advances in Science and Engineering, vol. 3, pp. 1-8, 2020.

[19] N. Levanon and E. Mozeson, "*Radar Signals",* New Jersey: John Wiley & Sons, 2004.

[20] G. Stimson, "*Introduction to Airborne Radar"*. New Jersey: SciTech Pub, 1998.

[21]M. Zhang, L. Liu, and M. Diao, "*LPI Radar Waveform Recognition based on Time-Frequency Distribution*" *Sensors,* vol. 16, pp. 1682-1702, 2016.