International Journal of Nanoelectronics and Materials
Volume 14 (Special Issue) December 2021 [165-173]

A Preliminary Study on Feasibility Radar Cross-Section of Foreign Object Debris for Size Classification

P N Ja'afar[1], S M Idrus[1] *, S Ambran[1], A Hamzah[1], N Zulkifli[1], N A Hamid[1], A Kanno[2], N Shibagaki[3], K Kashima[3] and T Kawanishi[4]

[1]Universiti Teknologi Malaysia, 81310 Johor Bahru, Johor, Malaysia
[2]National Institute of Information and Communications Technology, Tokyo, Japan
[3]Hitachi Kokusai Electric Inc. Tokyo, Japan
[4]Waseda University, Japan

ABSTRACT

In this paper, a preliminary evaluation study is conducted, which aiming to investigate the radar cross-section (RCS) value that is capable to be used as an input parameter for Artificial Neural network (ANN) backpropagation for foreign object debris (FOD) size classification. The experimental work procedure for dataset acquisition is described. The FOD simulator is used as the FOD target which is made of metal cylinder shape with nine various dimensions and its RCS is defined by using Maxwell's equation. The location varying backscattered electromagnetic field from each target is measured for RCS calibration purposes. It is found that by using the received signal from radar, which is the RCS of the target and its locations, it can be utilized as input parameters of backpropagation algorithms. The ANN classification application is to define its size by the ranges; small (-30.99 to -21 dBsm), medium (-20.99 to -11 dBsm), and large (-10.99 to 0 dBsm). The interference signal getting from measurement (22.46 to 25.2 dBsm) exhibited good reflectivity behavior. The acquired input showed to be useful for ANN for FOD size classification.

Keywords: artificial neural network, backpropagation, classification, FOD dataset, foreign object debris

1. INTRODUCTION

The term foreign object debris (FOD) is referred to any object, particle, or debris found on an airport runway or taxiway which does not belong there but has the potential to cause destruction or harm to aircraft that passes by. Based on Federal Aviation Administration [1], FOD is defined as debris or substance that does not belong there but has the potential to cause any damage and destruction to aircraft and flight operations. Because of FODs, few events have happened that affect undesirable significances. For instance, there are one of the tragic accidents happened in 2000, where the Air France Flight crashed almost instantly after take-off caused by the FOD broke the fuel tank [2]. Regardless of its size, the runway needs to be constantly monitored as FOD is indeed risky and must be removed to ensure safety and security.

To detect those FODs, some automatic detection systems based on various sensor devices have been developed and commercialized recently such as the Tarsier system by Qinetic, FODetect by Xsight, iFerret by Stratech the latest one FOD detection system by HiKE as summarized in [3]. Millimeter-wave (mm-wave) radar is the most frequently chosen as the sensor due to its detection performance such as high-range resolution, high sensitivity, and weather robustness [4–7]. Some of these systems also use a hybrid system that is equipped with mm-wave radar and a high-definition camera to visualize the detected FOD, and then, the images are verified by

*sevia@utm.my

Prior researchers have studies FOD detection and recognition using machine learning and deep learning approaches. FOD detection is to verify the existence of any debris found on the empty runway while FOD recognition is to identify what the FOD is. However, it is a great challenge to differentiate the size of objects that look very similar such as metal FOD of the same norm but different sizes. A bigger size of FOD can be easily seen on radar display as it shows high intensity, but smaller FODs have difficulties appearing due to its size that gives low intensity on radar position per indicator (PPI). Therefore, FOD size classification has much greater significance to give primary information of FOD before the personnel goes to the location to clear the FOD.

In recent years, artificial neural networks (ANN) [8] have exhibited effective classification of systems, e.g., in the robust target [9] and precipitation radar reflectivity [10]. A feedforward ANN with a multilayer perceptron, which has one or more hidden layers, has been discovered its capability of forming complex decision boundaries. When such a network is trained using a backpropagation learning algorithm, it is found to perform as a good classifier of different types of radar targets. The performance of the network in classifying has achieved between 80% up to 93.75% with all the training and testing processes [8–10]. The ability of backpropagation ANN to generalize after learning from examples has made it a very useful tool for pattern classification.

In this study, instead of focusing on the target pattern, we maintained the shape of the target using the FOD simulator that has a cylindrical shape but various measurements. Different dimensions give different radiated reflection power, in which the backscattered signal propagates at various RCS values. Hence, we emphasize the RCS value received from radar signal to be classified into three size range classification. Each category is limited to range 0 to -10.99 dBsm, -11 to -20.99 dBsm, and -21 to -30.99 dBsm for large, medium, and small range respectively. The measurement will be taken at various point locations to calibrate the target's cross-section.

2. ANALYTICAL DEVIATION OF FOD SIMULATOR

Before experimental work, the analytical deviation is required to define the radar cross-section (RCS) of FOD. Since FODs have unique features and shapes, it is challenging to derive their RCS. Hence, a simple geometry cylinder shape with nine different dimensions is used as a FOD simulator. The material is made of metal since it is the common crucial FOD found on runway besides has stronger signals that exhibit higher RCS value [8]. Fig. 1 illustrates the elements of simple geometry on FOD simulator design and the real image of it is shown in Fig. 2.

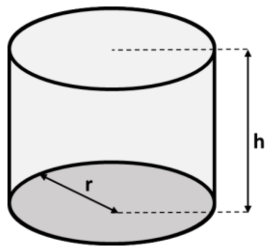


Figure 1. Design of FOD Simulator

Figure 2. FOD Simulators with nine dimensions

The relationship between electromagnetic field and RCS can be expressed by using Maxwell's equation [11]. This equation can validate the signal strength performance of an effective area that describes the intensity of the reflected signal. The backscattering cross-section is defined in (1):

$$\sigma_{max} = \frac{2\pi r h^2}{\lambda} \tag{1}$$

where r and h are the radius and height of the metal cylinder respectively, and λ is the wavelength of radar transmitted. The calculated σ_{max} is then computed in (2) to convert from true value into dBsm unit to standardize with measured value on the experiment.

$$10\, log_{10}\, (\sigma_{max}) \tag{2}$$

Based on its RCS values, the range size of FOD simulators is set into three size ranges; large, medium, small as presented in Table 1. It can be concised that the intensity of the reflected signal is dictated by the effective area of the target signals. The larger the effective cross-section area of the target, the greater the intensity of the reflected power signals.

Table 1 Maximum RCS value of FOD simulator

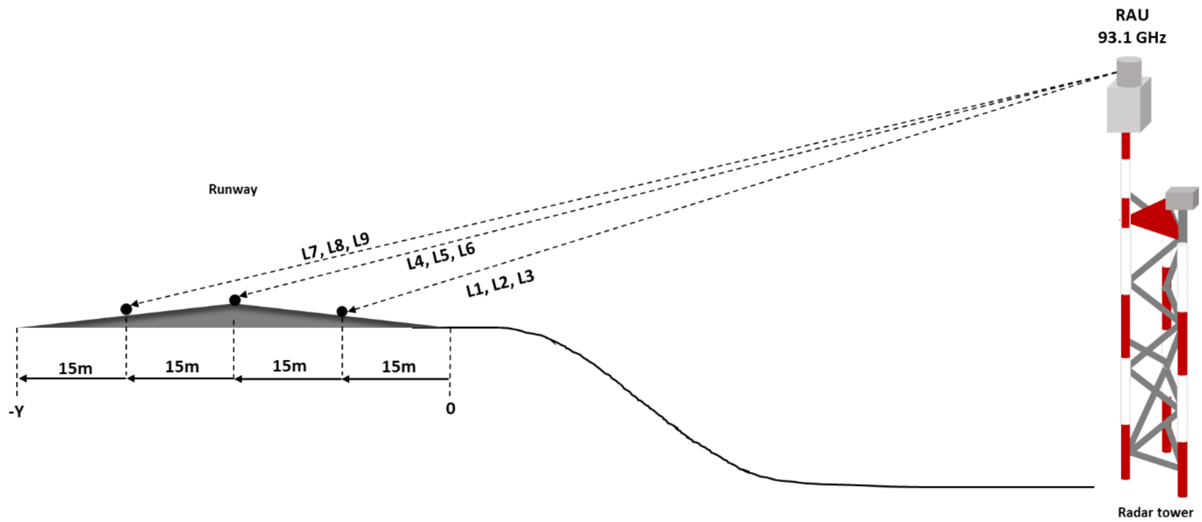
Range	#FOD	h (mm)	r (mm)	σ_{max}	RCS (dBsm)
Large	1	98	49.5	0.996	-0.02
	2	46	23	0.102	-9.92
	3	95	5	0.095	-10.24
Medium	4	30	20	0.038	-14.24
	5	42	7.5	0.028	-15.57
	6	21	10.5	0.010	-20.13
Small	7	11	15	0.004	-24.20
	8	6	20	0.002	-28.22
	9	10	5	0.001	-29.80

3. DATASET ACQUISITION

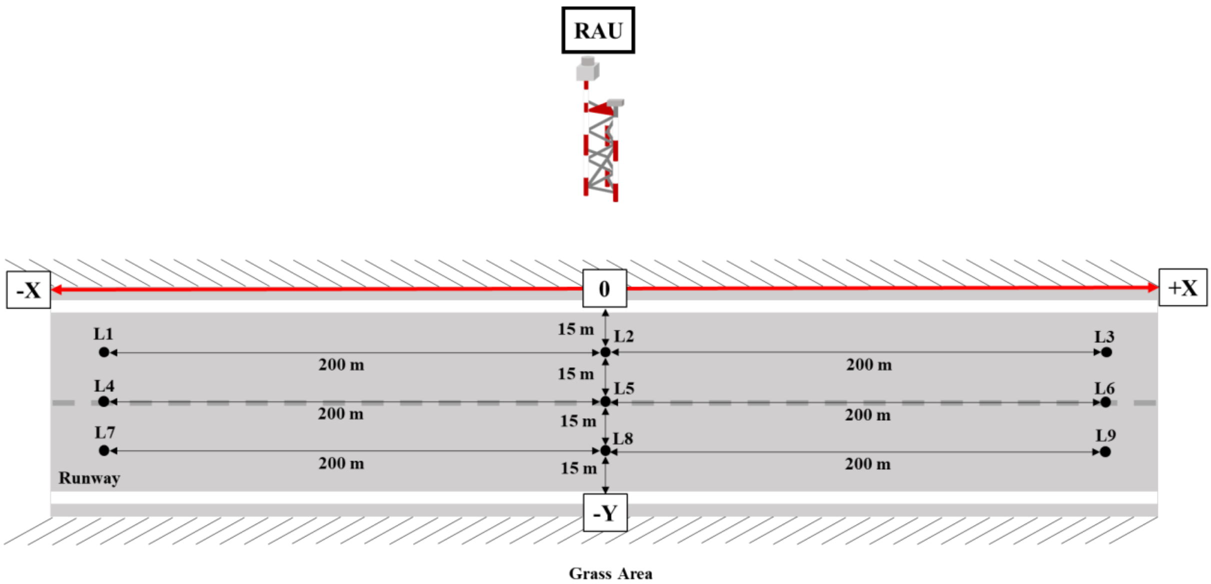
FOD dataset is required as it is the input parameter for machine learning to train the modeling. The datasets are constructed by conducting several experiments at the frequency 93.1 GHz at runway 2 Kuala Lumpur International Airport (KLIA). The real-time measurements are using

Frequency Modulated Continuous Wave (FMCW) radar as it performs high range resolutions and is immune to interference signals. In addition, FMCW can measure very small ranges of the target either in static or moving conditions [12]. The radar used is monostatic type radar as the transmitter and receiver antenna are physically located at the same location. The radar antenna unit (RAU) scans 360° rotation and is programmed to only collect data along the runway. The antenna transmitter yields electromagnetic wave through the air until it hit the FOD simulator that under trial. The antenna receiver received the reflected wave of the radar target as an echo signal, which is then stored in plan position indicator (PPI) for processing.

Nine measurements (L1 to L9) are conducted one at a time and its location. The location of L1 to L3, L4 to L6, and L7 to L9 are placed near RAU, the center of the runway, and near the grass area respectively as illustrates in the side view of the runway in Fig. 3(a). While Fig. 3(b) shows a plan view that describes the location where each dotted point represents one measurement in which, it is the position of P5 in arrangement Fig. 4.



(a)



(b)

Figure 3. Location of measurement (a) side view (b) plan view

In each measurement, nine identical sizes of the FOD simulator are placed in 3 by 3 form with a 10-meter interval. The FOD arrangement was placed to achieve more coverage area of the runway as well as differentiate the RCS of FOD at various locations. The measurements are initially conducted for Minimum Aviation System Performance Standard (MASPS) evaluation by The European Organisation for Civil Aviation Equipment (EUROCAE) to achieve system performance specifications [13]. Since the runway has a convex structure, the locations and arrangements are set to observe the backscattered radiation signal of the FOD simulator at various angles of the runway that are scanned by the radar.

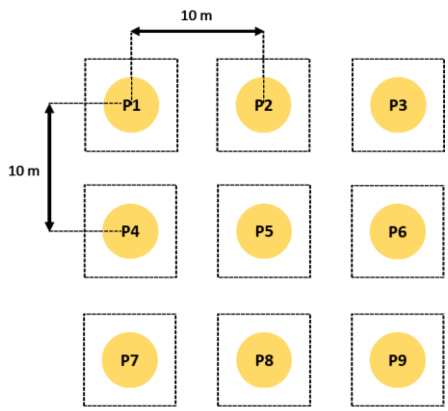


Figure 4. Arrangement of FOD Simulator

The measured RCS value from nine identical FOD will be compared to obtain an average value on each location, in which, one size of FOD simulator will obtain 9 datasets since we have 9 locations. The experiment is then repeated by measuring the RCS reflectivity with the other eight sizes of the FOD simulator at all locations. In total, nine sizes of FOD simulators will acquire 81 datasets considering nine locations. To obtain more datasets, the experiment is taken at another five RAU transmitted at 90-100 GHz frequency, and the total up to 486 datasets. All experiments are conducted under clear sky conditions to get consistent data.

4. ARTIFICIAL NEURAL NETWORK

This section explains how the input parameter is required to be normalized, the training and testing set division, and how the algorithm of the model works. The parameter used as input is received from the radar display which appeared on radar PPI. The inputs are including the RCS of FOD, the width, and the length of the runway.

4.1 Data Normalization

To get better quality of training data, data normalization is one of the essential components of ANN. Generally, data normalization is a pre-processing technique to accommodate different ranges and units of values in different dimensions [14]. Since RCS values consist of various numbers, this step is required to scale down the value that falls in the range between zero to one. Besides ensuring that all inputs are at a comparable range, pre-processing data can speed up the learning process and leads to faster convergence. The normalization formula is given in (3), where V is indicated as the value of input data which are RCS value, width, and length of the runway.

$$X_{normalized} = \frac{(X - X_{minimum})}{(X_{maximum} - X_{minimum})} \tag{3}$$

4.2 Training and Testing Dataset

The training set is one of the most important aspects of ANN [10]. Considering the normalized parameter extracted from radar signals for all six RAU, the 486 datasets are making use for training and testing the network. The amount for training and testing samples are randomly selected as long as the number of the training set is more than testing. This is because the training set will help the network to train and recognize the samples and to ensure the algorithm is supervised according to their label; small, medium, large, before giving the unlabeled data for testing or validation. 70:30 is one of the common ratios for the training and testing set. Hence, 114 out 486 samples for each class of FOD simulator, are for training, and the rest will be used for the testing sample.

4.3 Backpropagation

Backpropagation is a type of ANN used in solving classification problems as it is one of the supervised training methods. As illustrates in Fig. 5, the three-layer feedforward ANN framework is composed of the input layer, hidden layer, and output layer. The input and output layers are storing input and output data to the network respectively. While the hidden layer is a point of the backpropagation where the model works by sending data from the previous layer to the next layer. When the input of RCS value and its location is given to the network, weights are modified to minimize the difference in forms of the desired output. The training is done multiple times so that the whole input network can satisfy and generalize the output patterns, and achieve minimum error. Based on [10], [15], the results are promising that the backpropagation algorithm is easy to implement while keeping the efficiency of the network.

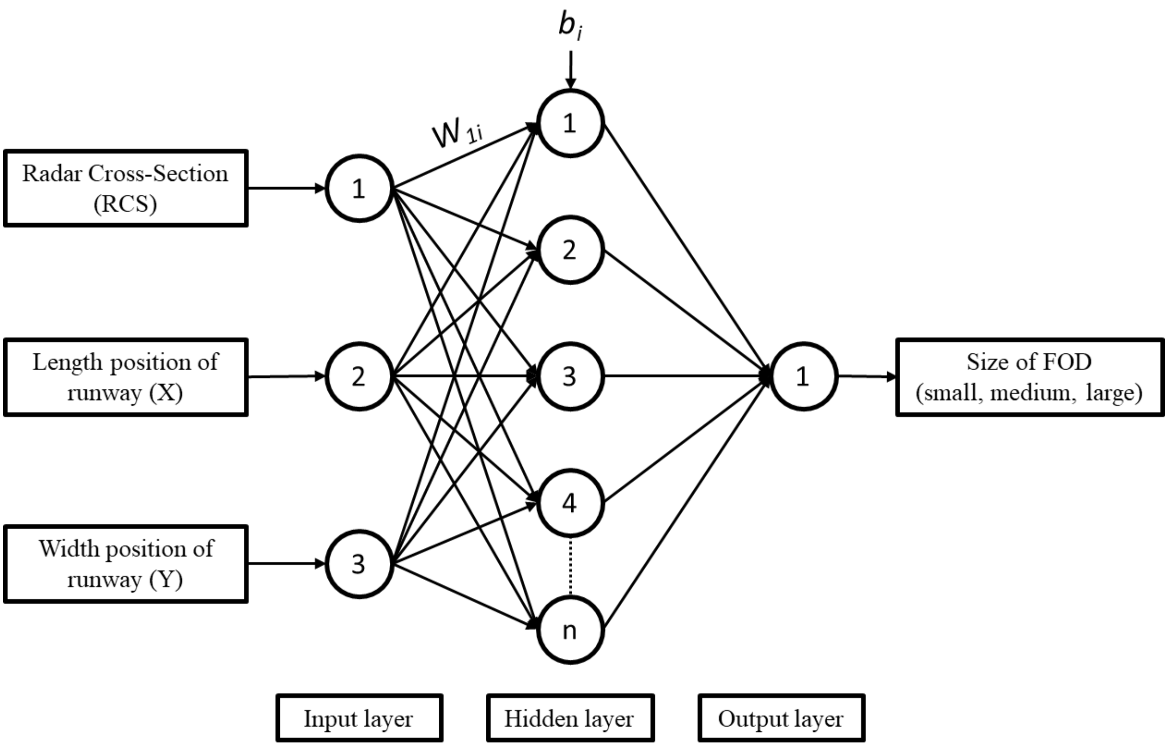
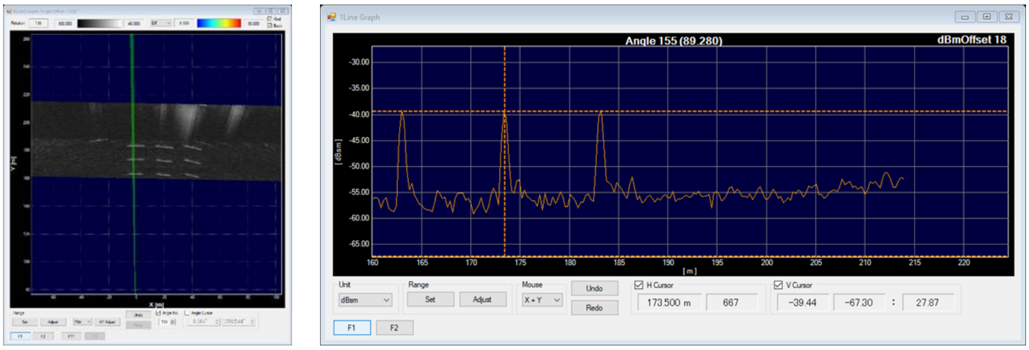


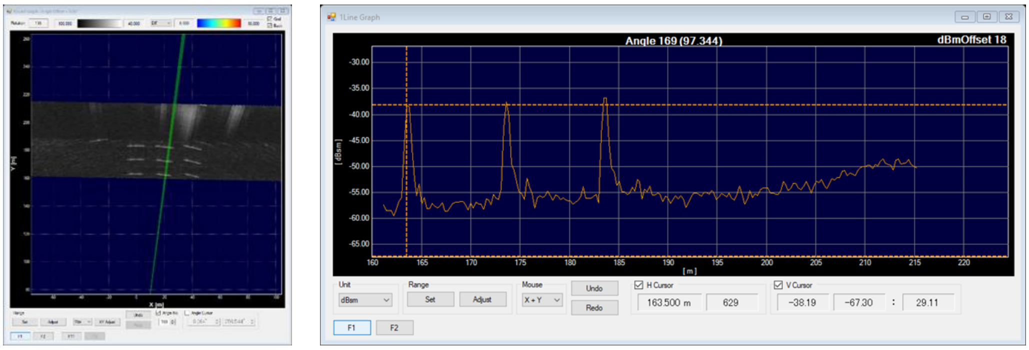
Figure 5. Framework of backpropagation ANN studied in this work

5. RESULTS AND DISCUSSION

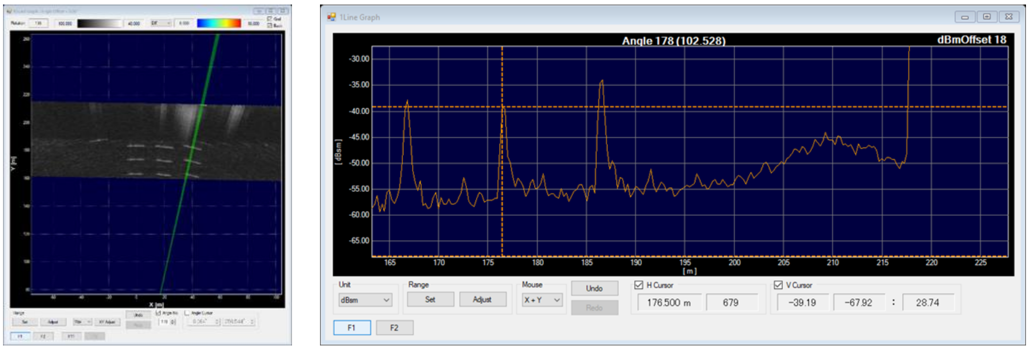
In this paper, the measurement conducted at L2 using FOD #4 is completed. Only FOD #4 is evaluated to acquire data collection of RCS value as it is the proof of principle. Further experiments will be done on FODDS but not mention here. In order to obtain the reflected signal and RCS values of three FODs in a row, the green line which indicates the radar signal propagation is adjusted at the center point of the reflected signal. The graph in Fig. 6 (a), (b), and (c) demonstrate the PPI images and line graph that are appointed at angles 155, 169, and 178 respectively. As can be seen in the line graph, the three peaks are indicating the three FODs at every selected angle.



(a)



(b)



(c)

Figure 6. PPI Image (left) and line graph (right) of FOD #4 detection at angle (a) 155 (b) 169 (c) 178

Based on the experiment, the measured RCS values are slightly different from the calculated values. To summarize the reflection power difference, Fig. 7 shows the plotted graph of both measured and calculated values. The reflection of measurement from the experiment is scattered within the range -36.7 to -39.44 dBsm which shows a difference of 22.46 to 25.2 dBsm from the calculated value. It was observed that the value has differed due to the actual measurement might be affected by the interference signal due to grass on the edge of the runway or the ground clutter.

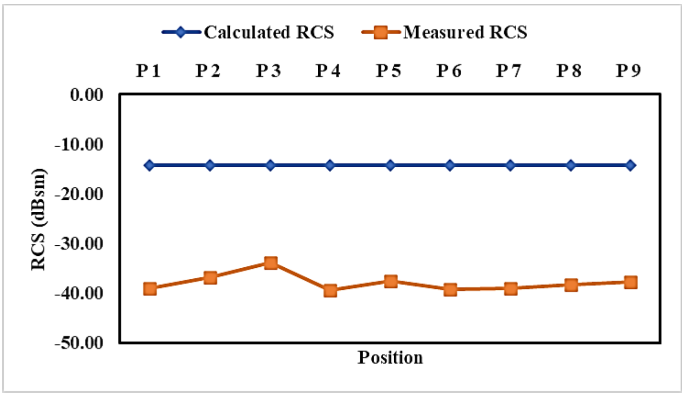


Figure 7. Plots of calculated and measured RCS value for FOD #4 at L2

6. CONCLUSION

This paper presented a simple experimental work conducted in the real field, which is on Runway 2 KLIA. A proper RCS measurement was characterized by measuring the backscattered radiation patterns in the FOD simulator at one location for evaluation. The reflected signal shown in PPI images and line graph is vibrant to understand. The obtained RCS patterns showed that the material of the FOD simulator used is adequate to describe its reflectivity behavior as a function of signal processing. The concept regarding classification is explained and the backpropagation algorithm is briefly described. For primary assessment to acquire the dataset, the measurement for one size FOD at one location has shown good reflectivity behavior. Even though the measured RCS differed from calculated values, it can be accepted by calculating the error, which is 22.46 to 25.2 dBsm due to its interference signal from the grass on the edge of the runway or the ground clutter. The obtained RCS measurement showed that this value can be used as input for FOD size classification utilizing the ANN backpropagation algorithm.

ACKNOWLEDGEMENTS

This work was conducted as a part of a collaborative project entitled "FODDS Field Trial at KLIA" funded by the Ministry of Internal Affairs and Communications, Japan, also supported by Universiti Teknologi Malaysia institutional grant 08G49 and iSmartUrus-UTM DTD vot 4C524. The authors would like to thank Malaysia Airport Holding Berhad, Hitachi Kokusai Electric Inc, Waseda University, NICT Japan, and iSmartUrus Sdn Bhd for their cooperation in the field experiments.

REFERENCES

[1] System Integration Study of Voice over Internet Protocol for National Airspace System Ground-to-Ground Communications Phase II Final Report, E. Col et al., (2009).
[2] Bureau Enquêtes-Accidents, Accident on 25 July 2000 at La Patte d'Oie in Gonesse (95) to the Concorde registered F-BTSC operated by Air France, d'Analyses pour la Secur. l'Aviation Civile. Fr., France, (2000) pp. 187.
[3] G. Fizza, "Line of sight visibility analysis for foreign object debris detection system," in J. Phys. Conf. Ser., vol. **1878**, no. 1 (2021) pp 1–3.

[4] S. M. Idrus, "Demonstration of 95 GHz Single RAU Linear Cell Radar over Fiber and Radar Propagation Study in Malaysia," in Prog. Electromagn. Res. Symp, (2018) pp. 1693–1697.
[5] A. Kanno, "Field trial of 95-GHz frequency-modulated continuous-wave radar system driven by radio over fiber techniques," in RAPID 2018 IEEE Res. Appl. Photonics Def. Conf., (2018) pp. 39–42.
[6] T. Kawanishi, "90-GHz Linear-Cell Systems for Public Transportation Systems," in Int. Conf. Transparent Opt. Networks, (2018) pp. 3–4.
[7] N. Mohamed, "All optical millimeter-wave signal generation and transmission for radio over fiber (RoF) link," in Indones. J. Electr. Eng. Comput. Sci., vol. **15**, no. 3, (2019) pp. 1428–1435.
[8] D. E. Rumelhart, "Parallel Distributed Processing," in Parallel Distrib. Process., (2019) pp. 319–361.
[9] S. Chakrabarti, "Robust Radar Target Classifier Using Artificial Neural Networks," in IEEE Trans. Neural Networks, (1995) pp. 760–766.
[10] W. Jing, C., "Classification of precipitation radar reflectivity echo with back-propagation ANN," in Proc. 2008 Pacific-Asia Work. Comput. Intell. Ind. Appl. PACIIA, (2008) pp. 630–633.
[11] H. J. Li, "Radar and Inverse Scattering", in Elsevier Inc., (2005) pp. 671–690.
[12] A. G. Stove, "Linear FMCW radar techniques," in IEE Proceedings F-Radar and Signal Processing (1992) pp. 343–350.
[13] Minimum Aviation System Performance Specification for Foreign Object Debris Detection System , 4th ed., T. E. Organisation, C. A. Equipment, O. Europ, and A. Civile, (2014) pp. 235.
[14] L. Yu, "Research on data normalization methods in multi-attribute evaluation," in Proc. 2009 Int. Conf. Comput. Intell. Softw. Eng. CiSE 2009, (2009) pp. 1–4.
[15] P. Sathya, "Classification and Segmentation in Satellite Imagery Using Back Propagation Algorithm of ANN and K-Means Algorithm," in Int. J. Mach. Learn. Comput., vol. **1**, no. 4, (2011) pp. 422–426.