FSR MARINE TARGET CLASSIFICATION WITH DATA MINING APPROACH

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Abstract: The purpose of this paper is to present the research results from a study focused on the possibilities for implementing data mining approach for classification of radar detected marine targets. The study is based on experimental data collected by researchers from Birmingham University with Bistatic Forward Scattering Radar. The data is further processed by using a CA CFAR approach for radar detection and target specific estimation, proposed by Sofia University team. Rough estimation of the target parameters in time domain in implemented, based on the hypothesis that the number of detected samples received from the target defines the target projection (length) and the energy reflected from the target. The classification models for predicting the class of the detected marine targets, achieved with selected algorithms in data mining software WEKA, for two values of the predicted variable (the marine target class), are described in the paper. The results from the evaluation of the models are compared with the results received in our previous paper, concerning classifiers achieved for predicted target variable with three values. The proposed hypothesis that the decreased number of values for the predicted variable will lead to achieving classifiers with better quality is validated.

1 INTRODUCTION

Forward scattering radar (FSR) is a special type of bistatic radars that operate in the narrow area of the forward scattering effect where the bistatic angle β is close to 180^0. FSR has some fundamental limitations: the absence of range resolution; operation within narrow angles ($\pm 10^0$). Due to the forward scattering effect (diffraction), the Radar Cross Section of a target extremely increases (by 2-3 orders) and mainly depends on the target's physical cross section and is independent of the target's surface shape and the absorbing coating on the surface. Forward Scattering Radar is effective for detection of "stealth" targets. The Doppler shift (radial velocity) of the target reduces when the target

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moves from the boundary of the forward scattering zone to the baseline "transmitter-receiver", equals zero when the target crosses the baseline and increases again as the target approaches the zone (see Fig.1 and Fig.2).

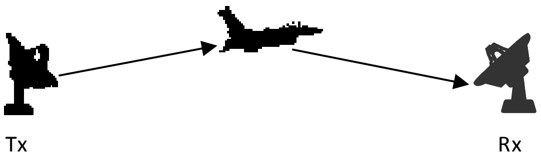

Figure 1: FSR system topology.

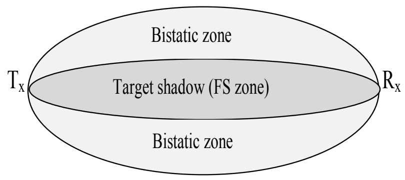

Figure 2: Coverage of BS and FS radar systems.

A team from Birmingham University has been working on these issues and considers different structures and algorithms for detection, estimation and classification of ground and marine targets in a Forward Scatter Radar (FSR) system in many published papers. They propose equations for calculating marine target parameters, i.e. velocity and length, on the basis of the estimated signal parameters (Cherniakov, Gashinova et al., 2007, Cherniakov, Raja, et al., 2005, Rashid, et al., 2008, Raja, 2005). One of these equations shows that the linear size of the target is proportional to the speed of movement of the target and inversely proportional to the first spectrum minimum. The time duration of the target signal is related in the FSR zone to the approximate profile of the object. Then, the precision estimation of the time duration of the Doppler signal is very important because it guarantees the quality of estimates of the frequency calculated on the first minimum and the maximum of the Power Spectrum Density. In our previous papers (Kabakchiev, et al., IRS, 2011, Kabakchiev, et al., SPS, 2011) we have considered a rough approach in time domain for calculating the length (time duration) and energy (FSR Radar Cross Section) of marine targets in a Forward Scatter Radar (FSR) system. The error of estimation of the target length is about 15-20% which is within the engineering accuracy.

The purpose of this paper is to present the research results from a study focused on the possibilities for implementing data mining approach for classification of radar detected marine targets. The study is based on experimental data collected by researchers from Birmingham University with the constructed by them Bistatic Forward Scattering Radar, as described in (Cherniakov, Gashinova et al., 2007). The collected data is further processed, by using the CA CFAR approach presented in (Kabakchiev et al., IRS, 2011, Kabakchiev et al., SPS, 2011), for achieving radar detection and target specific estimation development from Sofia University team. They use rough estimation of the target parameters in time domain, based on the hypothesis that the number of detected samples in the signal received from the target defines the target projection (length) and the energy reflected from the target. In our previous paper (Kabakchiev, Kabakchieva et al., 2011), the targets were distributed in three classes corresponding to three variants of detected marine objects (water-jets, boats, ships) that are crossing a maritime electronic fence (Cherniakov, Gashinova et al., 2007). The classification models for predicting the detected target class were based on the received and pre-processed target data and were built by applying different data mining methods. The WEKA software (Witten, 2005) was used for the Data Mining analysis. The achieved results from the classification, for the three classes of marine targets (MISL Boat, Average Boat, Big Boat) in time domain, were similar to the results achieved by Birmingham University team for speed and length estimates of ground targets in frequency domain.

The thorough analysis of the achieved results revealed that the trained classifiers for predicting the class of the detected marine targets based on the available signal data did not perform with high accuracy for all the three classes (Kabakchiev, Kabakchieva et al., 2011). The classifiers worked best for the MISL Boat class which was most represented in the available data, and much worse for the other two classes which were less represented in the data.

The purpose of this paper is to find an approach for increasing the classifiers' accuracy of prediction of the marine target class for the same dataset. Our hypothesis is that the accuracy of prediction will increase if the number of classes is decreased, i.e. by combining the marine targets from the two less represented classes into a single class. The classification models for predicting two classes of marine targets are described in the paper, using popular evaluation criteria for estimating the classifiers' quality. A comparison is also made between the classifiers achieved for the two variants of the predicted target variable – with three and two classes. The received results confirm the validity of the proposed hypothesis, showing that the decreased number of classes of the predicted variable lead to achieving classifiers with better quality. These results are comparable to the results achieved by the researchers from Birmingham University for classification based on the Doppler velocity (Cherniakov, Raja et al., 2005, Rashid et al., 2008, Raja, 2005, Ibrahim, 2009).

2 DATA COLLECTION AND MARINE TARGET ATTRIBUTE EXTRACTION

2.1 Data Collection

The experimental data is collected by the team from Birmingham University in February and March 2010. The experiment site and the MISL Boat used for the experiments are presented on Fig.3 and Fig.4.

Figure 3: The Experiment Site.

Figure 4: The MISL Boat used for the Experiments.

The signal detection and data processing are based on the experimental records provided by the team from Birmingham University.

2.2 Marine Target Attribute Extraction

Several target attributes are extracted from the experimental data, including target time duration (length or sample number), reflected energy (power) from the target, signal-to-clutter ratio, the level of correlation before and after pulse cancellation, etc. They are calculated at the output of an original structure of an MTI CA CFAR K/M-L processor in time domain (Kabakchiev, Kabakchieva et al., 2011).

Moving Target Indicator is a method to reject the radar clutter. If one pulse is subtracted from the previous pulse, clutter echoes will cancel and will not be detected. Moving targets change in amplitude from one pulse to the next because of their Doppler frequency shift. If one pulse is subtracted from the other, the result will be not enough non-cancelled residue power after cancellation. In our previous papers (Kabakchiev et al., SPS, 2011, Kabakchiev et al., IRS, 2011) we used a two-pulse MTI technique for removing of correlated sea clutter, because implementation of three pulse MTI algorithm further reduced the correlation, but the improvement is not as great.

After the MTI processing, an original *CA CFAR processor* is used. The original CA CFAR processor differs from the standard CA CFAR because it uses bigger distance between the test cell and the two reference windows (equal to the half cells of the biggest target).

Then a *K/M-L test* is implemented. When the time duration of the target (corresponding to the signal sample size) is unknown, the approach for automatic batch detection of binary samples is usually used - determining the beginning and the end of the target plot and then estimating the plot length. Two nonparametric tests are used – a K/M test for determining the beginning of the target plot and a nonparametric L test for determining the target plot end based on the number of detected zero values. The aim is to use this approach for estimation of the unknown length of the samples of marine targets.

The calculation of the number of samples corresponding to the detected target at the output of the K/M-L detector is performed with a standard mathematical operator in Matlab. The time duration of the Doppler signal is calculated by multiplying the number of samples by the value of the Pulse Repetition Time. The time duration of the target signal is equivalent in FSR to the approximate profile/length of the target.

The average Doppler target power estimate is formed as square of the average difference between the amplitude of the extracted Doppler target signal and the CFAR detection threshold. The average energy of the Doppler target is formed as a product of the time duration and the average power. A standard statistical average procedure in Matlab is used to calculate roughly the average estimation of the target energy or power.

Table 1: Dataset used for the Data Mining Analysis.

No	Variable Name	Variable Type	Values	Missing Values
1	Trial Date	Nominal	17/02/10 (43), 18/02/10 (10), 21/03/10 (14), 23/03/10 (13)	0 (0%)
2	Distance Between Radars	Numeric	Min=300m, Max=500m, Mean=330.6m, StdDev=57.22 (300m, 316m, 500m)	0 (0%)
3	Antenna	Nominal	A1/2/V/A2/1/V; A1/3/H/A2/1/H	0 (0%)
4	Weather	Nominal	Sunny (56), Gloomy (11), Raining (13)	0 (0%)
5	Wind Speed	Numeric	1 - 5.1 m/s	2 (3%)
6	Wind Direction	Nominal	SE (42), S (22), NW (1), SW (10), W (3)	2 (3%)
7	Boat Direction	Nominal	South (11), North (12)	57 (71%)
8	S/N Ratio Before PC	Numeric	0 – 93.04, Mean=37.246, StdDev=26.207	12 (15%)
9	S/N Ratio After PC	Numeric	0 – 65.59, Mean=17.937, StdDev=22.605	14 (18%)
10	Number of Pulses Before PC	Numeric	0 – 2557, Mean=1148.892, StdDev=720.049	15 (19%)
11	Number of Pulses After PC	Numeric	0 – 4361, Mean=863.424, StdDev=1113.801	14 (18%)
12	Correlation Before PC	Numeric	0.62 – 1, Mean=0.954, StdDev=0.099	17 (21%)
13	Correlation After PC	Numeric	0.008 – 0.982, Mean=0.676, StdDev=0.322	18 (23%)
14	Energy Before PC	Numeric	0 – 2.939, Mean=0.599, StdDev=0.712	14 (18%)
15	Energy After PC	Numeric	0 – 0.499, Mean=0.024, StdDev=0.067	13 (16%)
16	Target Variant 1 – 3 Classes Variant 2 – 2 Classes	Nominal	 BigBoat (11), MISL_Boat (62), AverageBoat (6) MISL_Boat (62), OtherBoat (17)	1 (1%)

For investigating the robustness of the MTI CA GFAR K/M-L detector in different marine situations, we use estimation on other parameters in the time domain. These are estimates at the output of the K/M-L detector including correlation coefficient and signal-to-clutter ratio. The correlation coefficient and the SNR parameter are calculated as a ratio between the two standard deviations of the detected package pulses after the CA CFAR filtering and the clutter from the tested window, with standard functions in Matlab.

3 DESCRIPTION OF THE DATA USED IN THE DATA MINING RESEARCH

The data received at the output of the MTI CA CFAR K/M-L processor is used for the data mining analysis. It is currently organized in a simple excel file, because the originally collected data to this moment is actually very limited. However, if the radar system is put into operation, it is assumed that large volumes of data will be collected and processed, and they should be arranged in a database or a data warehouse in order to be in a format that is suitable for further analysis.

The currently analyzed data contains 80 instances described by 16 features (see Table 1), including the target variable. It contains nominal and numeric variables, describing various aspects, including the distance between the radars used in the experiment, the antenna parameters, the weather conditions including the wind speed and direction, and the evaluated target parameters.

As it is shown in Table 1, there are a lot of missing values for some of the data features. This is either due to missing information from the trials data, or to difficulties in measuring those parameters.

The Target Variable is the detected radar target that has to be classified in order to identify it. The original trial data contains 14 different targets that have been recorded. However, since the available data for the analysis is very limited (80 instances), it is decided to organize the actual radar targets into limited number of classes.

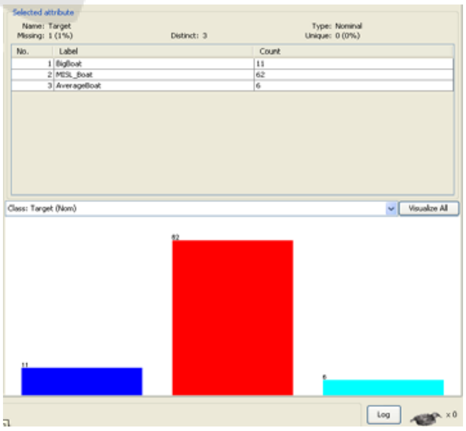

Figure 5a: Distribution of the Target Variable.

The research results presented in this paper refer to two variants of the target variable. In the first variant the target variable contains three distinct values (Kabakchiev, Kabakchieva et al., 2011) – MISL Boat, Big Boat and Average Boat, and in the second variant, presented in this paper, the target variable contains two distinct values – MISL Boat and Other Boat. The MISL Boat class includes data records about a small rubber boat, used for the experiments by the research team from Birmingham University, and that is the reason for having the majority of instances for this class of marine targets. The other classes are formed based on the expert opinion of the participants in the real experiments, and refer to larger boats in the Big Boat class, and to smaller boats in the Average Boat class.

The distribution of instances in the different classes, for the two variants of the Target Variable, visualization from WEKA software, is presented on Fig.5a and Fig.5b respectively.

Figure 5b: Distribution of the Target Variable.

4 DATA MINING ANALYSIS

The data mining analysis for the second variant of the predicted variable is performed by using the same research approach as in (Kabakchiev, Kabakchieva et al., 2011; Kabakchieva, 2013). The data mining classification task is implemented following the CRISP-DM (Cross-Industry Standard Process for Data Mining) approach (Chapman et al., 2000), because it is a non-propriety, freely available, and application-neutral standard for data mining projects, and it is widely used by researchers in the field during the last ten years. It is a cyclic approach, including six main phases – Business understanding, Data understanding, Data preparation, Modelling, Evaluation and Deployment. There are a number of internal feedback loops between the phases, resulting from the very complex non-linear nature of the data mining process and ensuring the achievement of consistent and reliable results.

The software tool that is used for the task implementation is the open source software WEKA, offering a wide range of classification algorithms (Witten, 2005).

Several different classification algorithms are applied during the Modelling Phase, selected because they have potential to yield good results. Popular WEKA classifiers (with their default settings unless specified otherwise) are used in the experimental study, including common decision tree algorithms - J48 (based on the C4.5 algorithm) and RandomForest, two rule learners (OneR and JRip), two Bayesian classifiers (NaiveBayes and BayesNet), a Neural Network (Multilayer Perceptron), and a SimpleLogistic algorithm.

Two *decision tree classifiers* are applied – *J48* and *RandomForest*. The J48 classification filter is based on the C4.5 decision tree algorithm, building decision trees from a set of training data using the concept of information entropy. The RandomForest is an ensemble classifier that consists of many decision trees and outputs the class that is the mode of the class's output by individual trees.

Bayesian classifiers are statistical classifiers that predict class membership by probabilities, such as the probability that a given sample belongs to a particular class. The two fundamental Bayes' algorithms are applied in the research work - *Bayesian networks* and *naive Bayes*. Naive Bayes algorithms assume that the effect that an attribute plays on a given class is independent of the values of other attributes. Bayesian networks are graphical models, which can describe joint conditional probability distributions.

Two algorithms for generating classification rules are considered. The *OneR classifier* generates a one-level decision tree expressed in the form of a set of rules that all test one particular attribute. The *JRip classifier* implements the RIPPER (repeated incremental pruning to produce error reduction) algorithm. Classes are examined in increasing size and an initial set of rules for the class is generated using incremental reduced-error pruning.

The *Multilayer Perceptron* (MLP) algorithm used in the research is a feed-forward artificial neural network model that maps the input data (input variables) onto a set of appropriate output (the target variable, or the defined classes in this case). MLP utilizes a supervised learning technique called back-propagation for training the network.

Logistic Regression is a well-known statistical technique that is used for modelling binary outcomes. A simple logistic regression is used for prediction of the probability of occurrence of an event by fitting data to a logistic curve. It is a generalized linear model used for binomial regression.

The *10-fold cross validation* test option is chosen for the classification algorithms implementation, because it proves to be very effective when the available data is very limited. Every time an algorithm is run, the available data is distributed in two data sets – training data containing 9/10 of the whole dataset, and test data including the other 1/10 of the data. Each algorithm is run ten times and the final results for the algorithm evaluation are calculated as average values.

5 THE ACHIEVED RESULTS

The classification models, generated with the selected data mining algorithms, for the two variants of the Target Variable, are compared by using the following evaluation measures: % of correctly classified instances, Kappa Statistic, True Positive (TP) and False Positive (FP) Rates, and ROC Area. These are well known measures for evaluation of data mining models for classification.

The results, achieved by applying selected data mining algorithms for classification of detected radar targets for the first variant of the predicted variable (with three values) show that the received overall accuracy of the classification algorithms is near 80%, although it differs for the three target classes (Kabakchiev, Kabakchieva et al., 2011). The data attribute Energy After PC is the attribute with the highest predictive power. The classification model with the highest accuracy of prediction is achieved with the Decision tree algorithm and it is easy to interpret and understand. However, that classifier performs best for the MISL Boat class and worse for the Average Boat and the Big Boat classes. The only algorithm that performs with similar accuracy of prediction for the three classes is achieved with the NaiveBayes algorithm.

Our hypothesis is that the accuracy of prediction will increase if the number of classes is decreased, i.e. by combining the marine targets from the two less represented classes into a single class. The results from the comparison of the classification models received for the two variants of the predicted variable are presented below.

The overall classification model accuracy is evaluated based on the % of correctly classified instances, and the classification error is based on the % of incorrectly classified instances. The results from the accuracy evaluation of the generated classification models are presented on Fig.6.

The results on Fig.6 reveal that all classifiers perform with accuracy above 70%. Moreover, the classifiers' accuracy for a Target Variable with 2 classes is higher than that for a Target Variable with 3 classes.

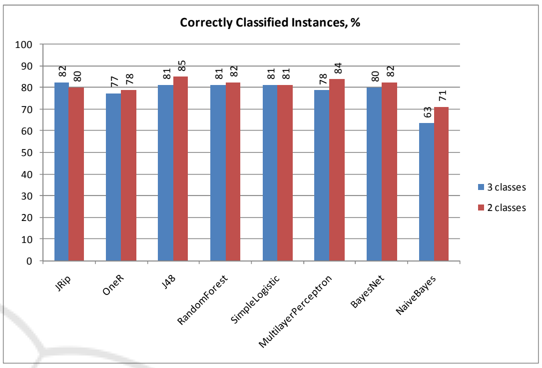

Figure 6: Accuracy evaluation of the generated classification models.

The results from the evaluation of the generated classification models, based on the Kappa Statistic evaluation measure, an index that compares correct classifications against chance classifications and taking values in the range from -1 for complete disagreement, to 1 for perfect agreement, are presented on Fig.7. Higher values are achieved again for the classifiers with the second variant of the Target Variable (with two classes). However, most of the values are quite below 0.5 which means that there is no high level of agreement between the predicted and the actual class of the targets.

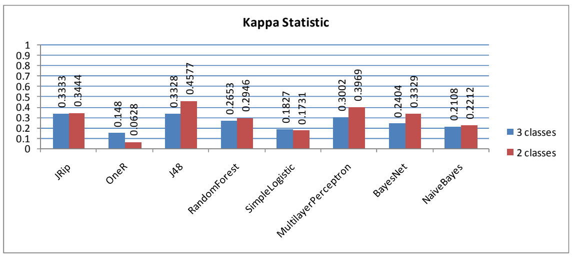

Figure 7: Evaluation of the generated classification models based on the Kappa Statistic measure.

The ROC curve plots the true positives against the false positives and the area under the curve represents the accuracy of the model – the larger the area, the more accurate the model.

Table 2: Detailed class accuracy evaluation of the generated classification models.

	Target Variable									
	Variant 1 - 3 classes						Variant 2 - 2 classes			
	BigBoat		MISL Boat		Average Boat		MISL Boat		Other Boat	
Data Mining Algorithm	TP Rate	FP Rate	TP Rate	FP Rate	TP Rate	FP Rate	TP Rate	FP Rate	TP Rate	FP Rate
JRip	0.182	0.029	0.984	0.706	0.333	0	0.903	0.588	0.412	0.097
OneR	0	0.029	0.952	0.824	0.333	0.027	0.984	0.941	0.059	0.016
J48	0.091	0.029	0.968	0.647	0.5	0.027	0.968	0.588	0.412	0.032
RandomForest	0.091	0.015	0.984	0.765	0.333	0.014	0.984	0.765	0.235	0.016
SimpleLogistic	0.091	0	1	0.882	0.167	0	1	0.882	0.118	0
MultilayerPerceptron	0.367	0.059	0.919	0.647	0.167	0.027	0.968	0.647	0.353	0.032
BayesNet	0	0.044	0.984	0.706	0.333	0.014	0.968	0.706	0.294	0.032
NaiveBayes	0.455	0.279	0.677	0.412	0.5	0.041	0.774	0.529	0.471	0.226

The achieved results for the ROC Area evaluation measure are presented on Fig.8.

For most of the classifiers the ROC Area values are slightly above 0.5 which means that they are not performing very well – slightly better than the naïve classification (random classification without the use of a classification model). The models generated with the Naïve Bayes and Random Forest algorithms seem to be the best performing classifiers (ROC Area values between 0.65-0.683), but these values are still not very high and consequently, the classifiers are not very reliable for correct prediction.

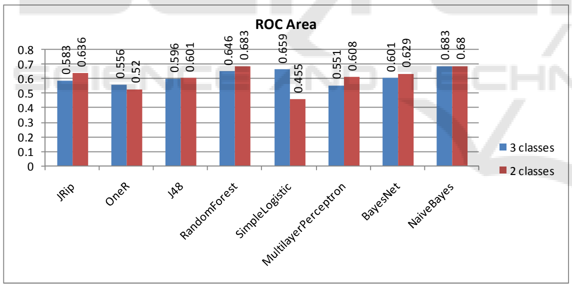

Figure 8: Evaluation of the generated classification models based on the ROC Area measure.

The results for the detailed class accuracy of the generated classification models are presented in Table 2. It is obvious that all classifiers perform with very high accuracy for the MISL boat class – the class that is most represented in the dataset, but are much less accurate in the prediction of the other classes.

6 CONCLUSIONS

All classification models generated with the selected data mining algorithms for the two variants of the target variable (with three and two values) perform with accuracies of prediction above 70% (the only exception is the NaiveBayes classifier achieved for a target variable with three values). Moreover, the classifiers received with the same data mining algorithms for a target variable with two values outperform the classifiers achieved for a target variable with three classes. All classifiers predict with very high accuracy the MISL Boat class – the class that is highly represented in the dataset, but are much less accurate in the prediction of the other (two or one) classes.

The classifiers achieved with the decision tree algorithm J48 are the best performing classification models in both cases, providing 81% prediction accuracy for a target variable with three classes and 85% prediction accuracy for a target variable with two classes. A very good classifier in the case of a target variable with two classes is also achieved with the neural network algorithm MultiLayerPerceptron – 84% accuracy, but this algorithm is not so effective in the case of a target variable with three classes. These are also the classifiers with the highest values of Kappa Statistic. However, these classifiers do not predict equally all classes, they perform much better for the prediction of the MISL Boat class, which is most represented in the data used for the data mining analysis, and are less accurate when predicting the other classes.

The classification models achieved with the NaiveBayes algorithm are the only classifiers working with closer accuracies of prediction for all classes, although these accuracies are not very high. The ROC Area values for these classifiers are also the highest received, which means that the classification models are properly working for all classes. However, the ROC Area and Kappa Statistic values achieved are still not very high and consequently, the classifiers are not very reliable for correct prediction.

The classification models achieved by applying selected data mining algorithms on the available data for FSR detected moving marine targets are similar to the results received by the research team from Birmingham University for FSR detected moving ground targets.

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REFERENCES

Chapman, P., et al. (2000). *CRISP-DM 1.0: Step-by-step data mining guide*. 2000 SPSS Inc. CRISPWP-0800. Available at: http://www.crisp-dm.org/CRISPWP-0800.pdf.

Cherniakov, M, Gashinova, M, Cheng, H, Antoniou, M, Sizov, V, Daniel, L.Y. (2007). Ultra wideband forward scattering radar: Concept and prospective. Proceedings of Int. Conf. Radar 2007, 1-5, (2007).

Cherniakov, M., Raja Abdullah, R.S.A., Jancovic, P., Salous, M. (2005). Forward Scattering Micro Sensor for Vehicle Classification. Proceedings of the IEEE International Radar Conference, Washington DC, US, pp. 184-189, 2005.

Galati, G. (edit.), 1993. *Advanced radar techniques and systems*, IEE Radar, Sonar, Navigation and Avionics Series 4, Peter Peregrinus Ltd.

Ibrahim, N.K.,. Raja Abdullah, R.S.A, Saripan, M.I. (2009). Artificial Neural Network Approach in Radar Target Classification. Journal of Computer Science 5 (1): pp.23-32, 2009, ISSN 1549-3636.

Kabakchiev, C., Garvanov, I., Cherniakov, M., Gashinova, M., Behar, V., Kabakchiev, A., 2011. *CFAR Detection and Paramiter Estimation of Moving Marine Targets using Forward Scattering Radar*, Proc. of Int. Radar Simp. IRS'11, Leipzig, Germany, (2011).

Kabakchiev, C., Garvanov, I., Cherniakov, M., Gashinova, M., Kabakchiev, A., Kiovtorov, V., Vladimirova, M., Daskalov,P, 2011. *CFAR BI Detector for Mariner Targets in Time Domain for Bistatic Forward Scattering Radar*, Pros. of Int. SPS-2011, Jachranka, Poland, 2011.

Kabakchiev, H., Kabakchieva, D., Cherniakov, M., Gashinova, M., Behar, V., Garvanov, I., 2011. *Maritime Target Detection, Estimation and Classification in Bistatic Ultra Wideband Forward Scattering Radar*. Conference Proceedings of the International Radar Symposium (IRS 2011), 7-9 September 2011, Leipzig, Germany, pp.79-84.

Kabakchieva, D. (2013). Study of Data Mining Classification Models. PhD. Thesis, Institute of Information and Communication Technologies (IICT), Bulgarian Academy of Sciences (BAS), 2013. Available at: http://www.iict.bas.bg/konkursi/2013/D_Kabakchieva/Dorina%20Kabakchieva%20avtoreferat.pdf

Raja Syamsul Azmir Bin Raja Abdulla (2005). Forward Scattering Radar for Vehicle Classification. PhD Thesis, July 2005, The University of Birmingham, UK.

Rashid, N, Antoniou, M, Jancovic, P, Sizov, V, Abdullah, R, Cherniakov, M, 2008. *Automatic Target Classification in a Low Frequency FSR Network*, Proc. of EuRAD conf. 2008, pp. 68-71.

Witten, I., Frank, E., 2005. *Data Mining: Practical Machine Learning Tools and Techniques*. Morgan Kaufmann Publishers, Elsevier Inc.