Ground Vehicles Classification using Multi Perspective Features in FSR Micro-Sensor Network

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***Abstract*—Automatic target classification (ATC) is examined from the viewpoint of improving classification accuracy. The challenge of automatic target classification is the selection of feature extraction (FE) technique, types of features and the type of classifier use. In this paper, the combination of Z-score and neural network (NN) is applied in order to perform the classification process for a ground target. The Z-score is used as a feature extractor where it will extract the significant data contain in the target's signal and NN acts as a classifier to classify the targets based on their size. Different types of features are used in order to optimize the system performance. Results obtained demonstrate the improvement of classification performance when high number of features in the classification is used.**

***Index Terms*—Neural Network; Principal Component Analysis; Feature Extraction; Forward Scattering Radar; Classification Accuracy.**

I. Introduction

Classification is a process or the act of dividing the data into a number of groups based on ways that they are alike. In recent years, there have been an increasing amount of literatures on classification in security system [1-4], biomedical applications [5-7] and military application [8-10]. However, there are limited amount of researches related to classification in radar using FSR micro-sensor network for ground target [4, 11, 12].

For ground target classification, there are various classification methods that have been used. In 2005, the first research on an automatic ground target classification was conducted [13] for operating frequency of 1GHz. The authors used PCA as the feature extractor and KNN as a classifier. They found that only the first few numbers of PCs are selected to represent the target. By combining PCA and KNN, a good classification performance could be obtained even with a limited number of data. However, problem arises when a large number of training data are used, which result in difficulties in calculating the distance between each instance of training data.

In [12], the ground target classification has been performed at lower frequency (64 MHz, 151 MHz and 434 MHz) where the same classification system is used as in [13]. It was proven that a good classification performance can be achieved even at low frequency. Later, a new classification system was proposed by [4] using NN where the input to NN is either manually added (in this case the author use the length of the target) or extracted using PCA. The result suggests that by using the input extracted from the PCA gives higher classification accuracy compared to manually added input.

Different approaches were used in [14]. The target's features were extracted using the PCA method and three other types of classifiers (Bayesian classifier, NN classifier and KNN classifier). The benefit of using multi perspective of classifier is to identify the most suitable method for classification. This paper concluded that the combination of PCA and NN give the best performance among the others.

The Neural network is once again being used in [15]. However, different input which consists of first main lobe width, second main lobe width and numbers of lobes are used and trained using multilayer perceptron (MLP) compared to [4] and these inputs slightly improved the classification accuracy.

In the classification system, feature is defined as a significant contribution to the overall appearance of the signal or object. Hence, [16] introduced Z-score as a new technique of feature extraction where Z-score chooses only significant data to be the input to the NN classifier. The result obtained shows a good performance where the NN training achieved 100% of classification accuracy (CA) at 64 MHz, 151 MHz and 434 MHz. However, for NN testing, the classification accuracy decreased at 434 MHz.

Based on the above papers, it is interesting to see the effect of multi perspective features in the classification system due to the fact that the target signal contains various features including significant and insignificant data. Hence, the main purpose of this research is to investigate the performance of classification when multi perspective features are used. Five types of NN models are used in order to identify the number of multi perspective features required for the classification.

The paper is organized as follows. It starts with the description of the classification system in section II and followed by the description of the classification method used in section III. Section IV discussed the results obtained and section V concluded this paper.

II. Classification System

In this paper, 200 measured signals with different types and sizes of cars are used; namely Car1, Car 2, Car 3 and Car 4. The dimensions of each car are tabulated in Table 1. Based on the previous studies [4, 11, 15], there are three important processes needed prior to target classification. These important processes are data collection, feature extraction and classification method and shown in Figure 1.

Table 1
Dimension of Car Used

Types of cars	Size of cars	
	Length (m)	Width (m)
Car 1	4.0	1.4
Car 2	4.5	1.4
Car 3	4.4	1.5
Car 4	4.8	2.1

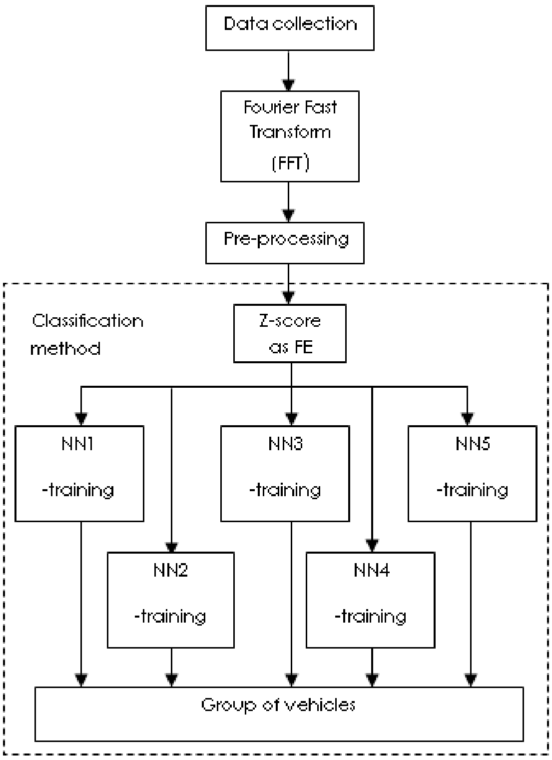

Figure 1: Proposed radar target classification

III. CLASSIFICATION METHOD

A. Z-score as Feature Extractor

Z-score selects significant data as the input to the classifier. The significant data of z-score is extracted based on the features of the signal. There are few steps need to be conducted in order to extract these features:

i. Calculate Z-score value

The Z-score value is calculated for a single value and indicates the distance of that value from the mean in units of standard deviation [16]. The Z-score value can be determined by using equation (1),

$$z = \frac{x - \upsilon}{\sigma} \tag{1}$$

where:
z = the value of Z-score,
x = value of the signal,
μ = mean of the signal,
σ = number of standard deviation of the signal.

The value of Z-score could be positive or negative value. The positive value indicates the value above the mean while negative value represents the value below the mean.

ii. Calculate Z-score value

Once the Z-score value is obtained, only the significant data is selected to be the input to the classifier. The significant data defined as data that give the positive value of Z-score. The data give negative value of Z-score indicates as insignificant data.

B. NN as Classifier

Neural Network classifies the target into their group based on their size. The selection of parameters, configuration and modeling is very important to ensure the high performance of the classification process.

i. NN modeling

Five NN models are created namely, NN1, NN2, NN3, NN4 and NN5. Each NN modeling used different types of features.

Figure 2 shows the example of block box modeling where only one type of feature is applied; in this case we are using target signal as the first type of feature. For different NN model, multi perspective of features can be used; for example crossing angle, crossing point, length of baseline and speed of targets.

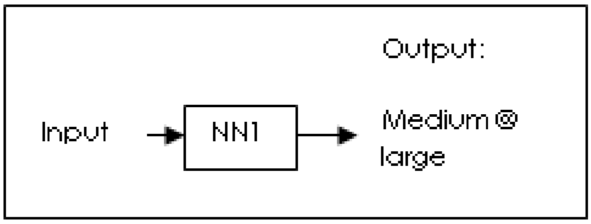

Figure 2: Black box modelling for NN1

ii. NN Architecture

There are three layer types in the NN architecture which are input layer, output layer and hidden layer. In order to construct the NN architecture, it is important to identify the parameters that need to be use especially the number of each layer type. For each NN, there is only one input and one out layer. For a hidden layer, the number of layer varies depending on the system. However, one hidden layer is sufficient enough to perform the classification [18].

Apart from the number of layer use, other parameter such as the type of training algorithm, activation function and back propagation need to be considered in order to achieve optimum classification performance. In this paper, the selection of the parameters are based on the previous works done by [4, 15, 17, 18] and listed in Table 2.

Table 2
NN Architecture for All NN Modelling

NN configuration	Values/Parameter
Input layer size	1
Output layer size	1
Number of hidden layer	1
Training algorithm	Levenberg marquat
Activation function	Tansig and purelin
Back propagation	Multi-layer perceptron

IV. RESULT AND DISCUSSION

For each NN model, there are two types of result obtained: the results from the NN training and results from the NN testing. The NN training is used to train the NN using data training while the NN testing is applied in order to measure the performance of NN if different data is used. This data is called a testing data.

Figure 3 and Figure 4 demonstrate the pattern of classification for NN training and NN testing at 434 MHz. The results shown are based on one type of feature. From Figure 3, we can see that the position of measured and predicted data are overlapping to each other. This indicates that there is no false target classification. Unlike NN testing as shown in Figure 4, there are few un-overlapping targets which indicate the false classification. The classification accuracy drops whenever the false classification occurs.

Figure 5 - Figure 7 show the classification performance for NN training and testing at 64 MHz, 151 MHz and 434 MHz, respectively. It is apparent from the figures that optimal performance can be achieved for NN training data. However, at 151 MHz, the classification accuracy decreases by 1% when lower than two types of features is used.

As for testing data, it can be observed that a good classification performance can still be achieved even though the performance is slightly lower compared to the training data. As we can see in Figure 5, the classification system achieves performance stability at 95% of accuracy if more than one type of feature is used. As for 151 MHz and 434 MHz, the classification accuracy increases as the number of feature increases. The highest classification accuracy is at its optimum (97% at 151 MHz and 96% at 434 MHz) when five type of features are applied.

There is no 100% true classification in the testing data. A possible explanation for this is that the number of features' type is not optimized. If more types of features are used, the classification accuracy might increase and the stability of the system could be obtained.

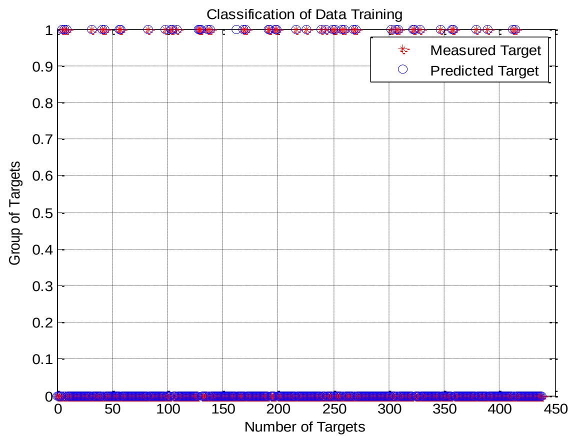

Figure 3: Classification pattern of data training at frequency 434 MHz when only one type of feature applied

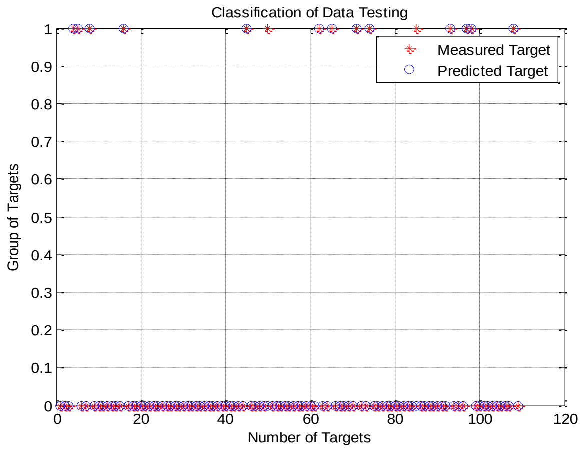

Figure 4: Classification pattern of data testing at frequency 434 MHz when only one type of feature applied

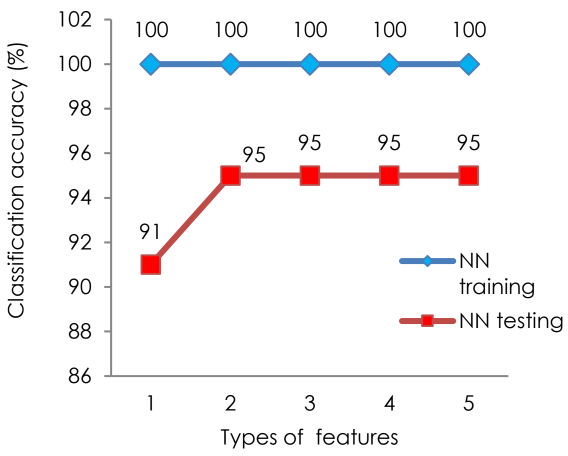

Figure 5: Classification accuracy for NN training and testing at frequency 64 MHz

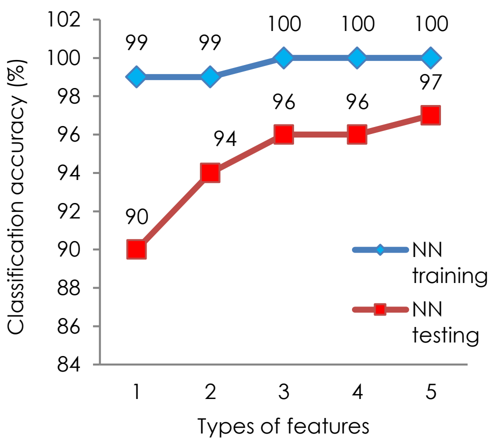

Figure 6: Classification accuracy for NN training and testing at frequency 151 MHz

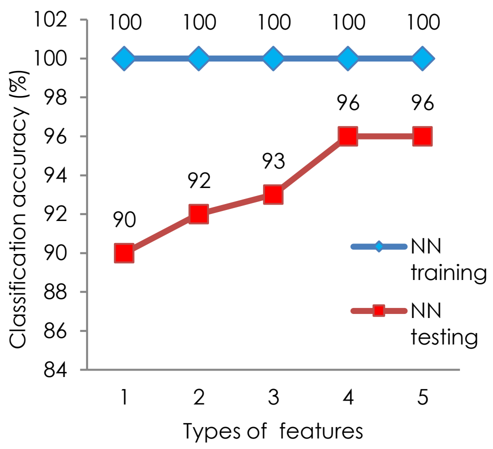

Figure 7: Classification accuracy for NN training and testing at frequency 434 MHz

V. CONCLUSIONS

The results obtained show that by applying multi perspective features, classification performance could be improved. As the number of features increases, the classification accuracy increases. The highest percentage of classification accuracy can be achieved when using NN5 system especially at 151 MHz. It is recommended that further research needs to be carried out in order to improve the classification accuracy, especially at frequency 64 MHz and 434 MHz.

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