Automatic Recognition of Ground Radar Targets Based on Target RCS and Short Time Spectrum Variance

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Abstract—**This paper presents a novel feature vector to be used with a robust automatic target recognition (ATR) classifier designed for a ground surveillance radar. A three element feature vector has been used where features are based on radar audio signal of 100 milliseconds duration. The short feature length allows fast real-time implementation of the classifier. Classification is done using a k-nearest neighbor (k-NN) classifier. There are two input classes to the classifier; automobile and pedestrian. Training has been done on real radar data. Classifier performance has been tested using test data from two different data sets. It has been demonstrated that in both cases, the overall classifier performance is above 80%.**

Keywords-automatic target recognition, ground surveillance radar, radar audio signal, micro Doppler phenomenon, k-nearest neighbour, feature extraction, classification

I. Introduction

The work described in this paper is aimed at developing an automatic target classifier for a coherent pulse Doppler ground surveillance radar*.

Automatic target recognition (ATR) is the next level of awareness of radar after target detection. The different approaches of ATR differ on the basis of radar waveform, range and cross-range resolution, and target motion (stationary or moving). A wide range of techniques have been applied to this problem [1]. Using the 1D range profile alone or augmented with cross-range profile to form 2D radar image of targets (SAR or ISAR) is the most commonly used approach for solving the automatic target recognition (ATR) problem. Such techniques are suitable for large targets such as ships and aircrafts. They are based on the radar cross-section (RCS) distribution of the various scattering centers on a target. A common problem with these techniques is that they require high range resolution radar having a resolution of the order of 1 meter or less [1]. Also, range profile is highly dependent on target aspect and requires good range resolution [2]. This approach is more suitable for static targets. For moving targets, motion compensation algorithms are employed to cancel the effect of motion [3].

For moving targets, a common radar detection technique is to utilize the Doppler effect wherein the target velocity causes a shift in the frequency of the radar carrier signal. This frequency shift can be translated to the speed of the main body of the target through a linear transformation. Typical ground radar targets such as pedestrians, helicopters, and tracked and wheeled vehicles have movable extensions or structures on the main body which have individual vibrating or rotating motion. This motion appears as a frequency modulation on the Doppler induced by the main body of the target. This phenomenon is called the micro Doppler effect [4]. The resultant micro Doppler signature generated by radar targets belonging to different classes is unique. Exploiting this uniqueness for automatic target recognition is a promising area of research.

For the pulse Doppler ground surveillance radar under discussion, the baseband audio signal falls within the audible frequency range. The radar audio signal holds a good prospect to be utilized for target recognition. This is evident from the fact that until some three decades ago, the only method of radar target classification was that a radar operator classified the target after listening to the target audio for a few seconds [5]. The advantage of this classification approach is that it does not require high range resolution. Also, the audio signal bandwidth requirement is low. However, its disadvantage is that a trained operator is required for target recognition. In addition, the operator can make the decision only after listening to the target audio for a time duration which exceeds the radar dwell time. As a result the radar cannot operate in scan mode during classification; it has to maintain a single look direction.

In this paper, a novel feature vector generation approach has been proposed for the ATR problem. The short feature vector length aids in fast classification and can be used in real time implementation. This robust classifier enables the radar to classify the detected targets in sector scan or full $360°$ scan mode.

Section II gives an overview of the various approaches which have been adopted in literature for feature extraction from radar audio signal. Section III details the features which were selected for classification in this work along with their

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motivation. Section IV gives a description of the radar data used in classification. Section V describes the classifier and training procedure. Performance of the classifier after experimental testing is given in Section VI followed by concluding remarks in Section VII.

II. Overview of Different Approaches Towards Feature Extraction For Automatic Target Recognition

Target recognition in case of radars consists of three main steps. The first step is to transmit a known signal which interacts with the target and a part of it is reflected back towards the radar receiver. This backscattered signal containing target signature is the input to the target classifier. The second step is extraction of features of interest from the target signature. The selection of features to be used for classification is an important step on which good performance of the classifier relies. The selected features should have the capability to differentiate among the classes under consideration. The feature vector extracted from the signature is then passed on to the third step which is the classification stage. The classifier requires a training data set in which feature vectors of known target classes are present. The new unknown feature vector is compared with the training data set entries according to the selected classifier scheme and decision about the class of the unknown test feature vector under question is made according to the rules of the classifier.

Different approaches have been used in the literature for feature extraction from radar target audio signal. Linear AR (autoregressive) coefficient estimation and time series prediction have been used by [6] for classification using radial basis function neural networks. Reference [7] has used the actual radar audio signal as a feature vector for input to k-nearest neighbor (k-NN) classifier. Alternately, DTW (dynamic time warping) technique, adopted from speech processing, has been applied to radar audio signal. In [8] the spectrum of the radar audio signal has been used as a feature vector which, after dimensionality reduction through PCA, has been classified using a naive Bayesian classifier. In [5], a similar (Doppler) spectrum of the radar audio signal has been classified using a Fisher Linear Discriminator [9].

This work aims at distinguishing between automobile and pedestrian targets. This paper proposes an ATR method that uses short length range bin slow-time data [10] of duration 100 milliseconds (which is less than the radar dwell time). Although speed of the target can also be used as a crude threshold for discrimination between the two target classes, that approach is bound to fail for low speed automobiles. This was one of the motivations for developing a reliable automatic target classifier which will perform classification independent of target speed. We have extracted three features from the radar audio signal and employed a k-NN classifier for classification of target into either of the two classes. The classification stage comes after the detection stage. Therefore, a separate class of 'no target' has not been defined. The next section describes the various features which can be used by a classifier for classification between pedestrians and automobiles along with the motivation for adopting the selected features.

III. Feature Extraction From Radar Audio Signal

As mentioned in the previous section, the incoherent audio data vector can be used as a feature vector. The major problem with this approach is that a small difference in the phase of signals belonging to the same class will result in a large distance in feature space. Secondly, as the data vector is a sinusoidally varying signal having frequency which corresponds to the target Doppler, the correlation between two signals reflected from two targets of the same class will decrease with an increase in the difference between their respective speeds. This will also result in a larger distance between two signals of the same class in feature space.

The above mentioned techniques have benefited from the underlying structure of the radar audio signal explained by the micro Doppler phenomenon. Because of the difference in the sources of modulation caused by the micro Doppler effect, the spectrum of targets having different physical structures differs from one another. This difference can be used as a basis of feature generation for target recognition using classification. It is pertinent to specify here that the radar signature of a target having micro Doppler motion is non-stationary [11]. However such signals can be treated as piece-wise stationary. In this work, signal of duration 100 milliseconds has been used for feature extraction which is short enough to be considered stationary for automobile and pedestrian targets.

The following features have been used to form a feature vector for this classification scheme:

A. *Variance in Target Doppler*

This feature makes use of the above mentioned micro Doppler phenomenon. Figure 1 shows typical single sided automobile and pedestrian spectrums.

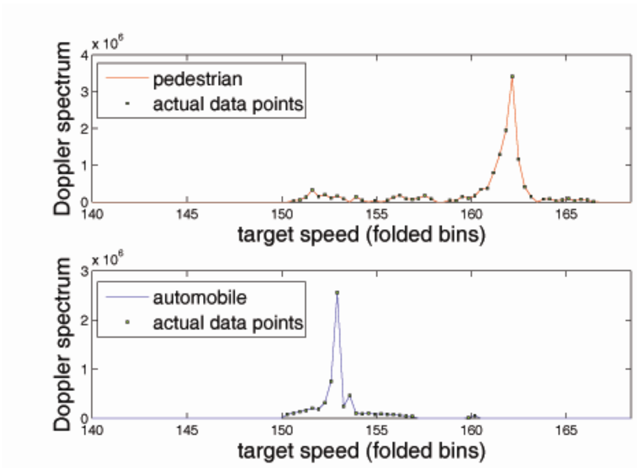

Figure 1. Spectrum of typical pedestrian and automobile target

In case of automobile, there is one sharp frequency peak corresponding to Doppler induced by the main body. However, in case of pedestrian, the Doppler induced by the target body is spread over several bins. This is a result of the modulation of micro Doppler signal on the Doppler induced by the main body of the pedestrian. This micro Doppler signal is generated as a result of vibratory motion of pedestrian limbs. As a result, there will be a larger variance in the Doppler spectrum of the pedestrian signal about the main body Doppler as compared to the automobile signal spectrum. This observation led to the use of variance in target Doppler as a feature vector. No discrimination has been retained between approaching or receding targets in the formation of this feature.

B. Average Power of the Radar Audio Signal

According to the radar range equation [12], for a particular radar receiving backscattered signal from targets belonging to different classes, the system parameters will be constant. Hence the received signal power will be directly proportional to the radar cross-section (RCS) of the two targets. Because of the difference between the RCS of the two target classes, there will be considerable difference between their respective average signal powers at a constant distance from the radar, which is a good basis for feature formation. Based on this reasoning, average power of the radar audio signal has been used as a feature.

C. Target Range

Using average signal power as a feature without taking into consideration the range of the target will confuse the classifier because average power of different targets is comparable for targets at similar range from the radar. For this reason, target range has been used as a feature to ensure that targets belonging to nearby range bins will be given more weightage in the classifier decision.

The aim of this work was to employ a small feature vector for this classification problem. The above mentioned robust features are consistent and proved be good basis for classification as shown by the classifier results.

IV. Data Description

A. Recorded Data Description

For classifier training and testing, real radar target audio signal was captured by the ground surveillance radar for several automobile and pedestrian targets in a controlled environment. From the raw data, slow-time data of duration 100 milliseconds taken from individual range bins under observation containing a valid target were extracted. The data duration was limited on the lower end by good classifier performance and on the upper end by the dwell time of the radar as well as the stationarity assumption. Preprocessing of the data included clutter filtering to remove clutter power. This was done to avoid obscuring of the weaker target signal by the stronger zero Doppler clutter signal.

B. Training Data Description

Separate data was collected for training and testing purposes. The objective was to verify classifier robustness. In the training data (dataset # 1), the automobile speed ranges from 10-40 kilometers/hour and typical pedestrian speed is 5-7 kilometers/hour. For both the target classes, data from all range bins under observation has been included in the training data. In the testing data (dataset # 2), signal of automobile moving with the speed of pedestrian has also been recorded. Data over the same range bins as in the training data has been included in the testing data set.

V. Classification Using k-Nearest Neighbour

A. k-Nearest Neighbour Classifier

In this work, k-NN classifier has been used for classification. Feature vector normalization has been done prior to training so that all features are given equal weightage. For each test vector, the classifier computes its Euclidean distance from all the available training vectors in the feature space. The value of k has been set equal to 3 in the case of two input classes. The class of the test data vector is declared based on majority voting among the respective classes of three training dataset instances closest to the test data vector in feature space.

B. Classifier Training

As mentioned in the previous section, the data from dataset # 1 was used for training and data from dataset # 2 was used only for testing the classifier which gave a measure of robustness of the classifier. This was achieved by testing the classifier with dataset # 1 and then the classifier result was compared with the result of same classification procedure applied to dataset # 2.

Following the rule of thumb used in classification theory, 90% of the data from dataset # 1 was used for training and 10% was used for testing purposes. Both classes have an equal distribution in the training data. Each training data instance contains signal from a time-range bin containing a single target belonging to either of the two classes (but not both).

VI. Experimental Results

The experimental test data collected in radar field trials contains instances corresponding to the two classes in an equal number so that the overall classifier performance gives a fair measure. In the first stage, the classifier was tested using test data vectors from the same data set. The overall success rate of the classifier given by the ratio of number of correct classifications to the number of input test instances was seen to be 82%.

The classifier performance in the form of a confusion matrix where the performance for individual classes can be seen is shown in Table. I.

TABLE I. Confusion Matrix for k-NN Classifier performance for dataset # 1

Input Class	**Declared as**	
	Automobile	***Pedestrian***
Automobile	75.8 %	24.2 %
Pedestrian	11.1 %	88.9 %

Next, the classifier was tested with dataset # 2 which had been recorded separately. The overall classifier performance of 84% clearly indicates robustness of the classifier for different testing conditions.

The confusion matrix for this test (shown in Table. II) indicates that the classifier performance has improved for automobile identification and shows some degradation in case of pedestrian identification.

TABLE II. CONFUSION MATRIX FOR K-NN CLASSIFIER PERFORMANCE FOR DATASET # 2

Input Class	Declared as	
	Automobile	***Pedestrian***
Automobile	83 %	17 %
Pedestrian	15.5 %	84.5 %

VII. CONCLUSION

In this paper, a novel feature extraction scheme has been suggested for automatic target recognition of ground radar targets. Two target classes i.e. pedestrian and automobile were considered. The suggested feature extraction scheme extracts three features from target audio Doppler which are based on average target power, target range and variance in target Doppler. k-nearest neighbor classifier has been used to perform target classification based on these features. The experimental results demonstrate that even with a small feature vector, the classifier has shown good performance. This is an indication of the robustness of the features which resulted from feature selection based on an understanding of the physical nature of the radar audio signal. These results also indicate that the difference in the spectrum of the two target classes caused by the micro Doppler phenomenon is a reliable basis for classification and future work will be in the direction of exploiting the properties of micro Doppler signature.

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