Radar target identification using various nearest neighbor techniques
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ABSTRACT
Radar target identification using decision-theoretic distance based methods have long been used for classifying unknown non-cooperative radar targets using their Radar Cross Section (RCS). This study revisits this subject using the recently developed Large Margin Nearest Neighbor (LMNN) technique in addition to other traditional nearest neighbor methods. Radar target recognition has been defined by two performance limiting issues namely 1) azimuth ambiguity (and/or erroneous estimation of target azimuth) and 2) presence of extraneous scatterers along the target. This study examines these different scenarios and highlights any of the benefits that LMNN may add to the radar target classification problem.

Keywords: Nearest Neighbor, Large Margin, Radar, Target Identification

1. INTRODUCTION
Classification using decision-theoretic techniques has long been explored as a viable option for stepped-frequency radar target recognition using radar cross-section (RCS) measurements. Classification can be performed using the raw RCS data, or can be implemented after feature extraction assuming certain scattering models. Although some of the models of radar backscatter can generate features that are relevant to the geometrical structure of the target, such techniques do suffer from the same drawbacks as raw-data classifiers. So, the issue addressed in this paper concerns radar target recognition in scenarios where azimuth knowledge is restricted, or the target time reference is not available, or the receiver is not coherent to warrant the use of phase and magnitude information in the recognition process. These concerns have an impact on recognition performance regardless of the implementation of sophisticated model-based feature extraction. The decision theoretic techniques used in this study involve the optimal approach (using the maximum likelihood technique assuming accurate statistical attributes) and using the distance based techniques such as the nearest neighbor approach. A relatively recent development of the nearest neighbor approach termed large margin nearest neighbor [1] is tested using radar backscatter. The nearest neighbor technique could be optimal if the noise statistics are identically distributed Guassian.

1.1 Stepped-Frequency Radar Backscatter
The radar system used in this paper is a stepped frequency radar in which an in-phase and quad-phase signal interrogates a model target in an anechoic chamber and the backscatter is recorded as amplitude and phase (or real and imaginary components). The frequency is then stepped up and another measurement takes place etc. The specific data used will be discussed later, but the frequency band is wide enough relative to the size of the target to consider this system as an ultra-wideband system capable of resolutions sufficient to discern various target scattering centers. The frequency response of the backscatter has been modeled as

\[ H(\omega) = \sum_{k=1}^{K} a_k (j\omega)^{n_k} e^{-j\omega t_k} \]

where K represents the number of scatterers \( t_k \) indicates the location of the k-th scatterer and \( n_k \) shows the degree of frequency dependence of the k-th scatterer and \( a_k \) is its amplitude. The inverse Fourier of the frequency response represents the target’s impulse response (or often known as the transient response or down-range profile) [3] and is given by

\[ h(t) = \sum_{k=1}^{K} a_k \delta^{n_k}(t - t_k). \]
The impulse response which indicates that a radar target can be modeled as a group of scatterers implies knowledge of the relative position of these scatterers with respect to a zero-time reference. The same expression for $h(t)$ can be regarded as a down range profile of the target using the relation

$$r_k = \frac{ct_k}{2}$$

where $c$ is the speed of light. Therefore, the zero-time reference may correspond to a physical point along the target. This target model, though not directly used in this study, brings forward several target recognition issues that affect the overall radar target classification performance.

### 1.2 Classification Issues

Whether attempting to classify the target using decision-theoretic non-parametric techniques or using parametric approaches, the following issues will have a profound impact on the classification performance. Even if we use methods relying on genetic algorithms, swarm techniques, fuzzy systems, or neural networks, these issues remain relevant:

- **Azimuth knowledge or ambiguity** has a profound impact on performance. Unlike classifying images or audio signals, the backscatter changes significantly when the target azimuth (or aspect angle with respect to the radar) changes. This is the case because the electromagnetic signature of the target is different at different aspect angles. Therefore, it is important to know whether the target azimuth is known exactly, or is unknown within a cone of uncertainty, or is totally ambiguous. Elevation could also be an issue, but it is not considered in this study.

- **Knowledge of zero-time reference** can have a significant impact on classification. This represents the difference between a classifier that knows the exact position of the scatterers along the unknown aircraft, or only knows the relative position of the scatterers. The choice of the classifier is influenced by the knowledge of zero-time reference. This essentially represents the difference between a target whose profile might be circularly shifted in time to an arbitrary position compared with the profile stored in the library or training files.

- **Knowledge of the backscatter amplitude and phase** is essential for knowing the target zero-time reference, but there are situations where the radar receiver is an incoherent system with only the target’s backscatter magnitude available for classification. This could be the case whether the time reference is known or not. There is, naturally, a difference in classification performance between classifiers utilizing all backscatter information and those relying only on the magnitude of the return.

- **Presence of extraneous objects or scatterers** within the vicinity of the unknown target. These objects may represent un-catalogued scatterers on the target or unlabeled disturbances in the range of the target. In fact, a target that releases a missile may change its electromagnetic signature relative to the catalogued signature. The number of extraneous scatterers may vary depending on the target structure and radar bandwidth. Extraneous scatterers are also dependent on the azimuth of the target with respect to the radar.

- **Statistical distribution, stationarity assumption, and time-dependence** can also have a profound impact on the classification system. Assuming a certain statistical model and being able to estimate its parameter may help in utilizing optimal classification methods. Also stationarity of the return backscatter is a relevant factor. Furthermore time-frequency dependence of the recorded return may also have an impact on recognition performance. Furthermore, the assumption of having correlated or uncorrelated noise (Gaussian or otherwise) would influence performance even with complete knowledge of correlation parameters.
2. CLASSIFICATION METHODS

2.1 Maximum Likelihood Approach
This is the optimal approach that can be used as a benchmark for assessing other techniques. This approach requires exact knowledge of noise statistics (including all parameters), exact knowledge of priors, and exact knowledge of distribution. The idea is to maximize the a posteriori probability that a class $\omega_n$ is likely given the observation vector $X$, $P(\omega_n / X)$. This is equivalent to maximizing

$$P(\omega_n / X) = \frac{p(X / \omega_n)P(\omega_n)}{\sum_{k=1}^{N} p(X / \omega_k)P(\omega_k)}$$

Which requires knowledge of distribution $p(.)$ and a priori probabilities $P(\omega_k)$ of all classes. In the case where the target azimuth is known within a certain range the distribution is found as a mixed Gaussian using

$$p(X / \omega_k) = \frac{1}{N_s} \sum_{m=1}^{N_s} p(X / \omega_k, \theta_m)P(\theta_m)$$

Where $P(\theta_m)$ represents the a priori probability of the azimuth angle $\theta_m$ assuming a total of $N_s$ catalogued subclasses $N_s$. Clearly, using an optimal classifier requires exact knowledge of numerous parameters especially when there is azimuth ambiguity.

2.2 Nearest Neighbor
Despite its simplicity, this technique [4] is a powerful classification tool that can be optimal if the additive noise is white Gaussian and there are no azimuth ambiguities. Studies have shown that this technique yields near optimal results even when there is azimuth uncertainty but it fails when there is lack of knowledge of target zero-time reference and/or extraneous un-catalogued scatterers. The idea is to simply minimize the Euclidean norm between the measurement vector and the catalogue of the k-th target at azimuth $\theta_m$

$$d_m = \min_k \| X - C_{k,\theta} \|$$

Alternatively, the k-nearest neighbor assigns the measurements to the most common class among its k nearest neighbors.

2.3 Large Margin Nearest Neighbor
Large margin nearest neighbor technique was developed by Weinberger et al [1,2] where convex optimization was used to define margin criterion where exemplars from different classes have large margins while the k-nearest neighbors are of the same class as the training exemplar [1]. Loss functions that place heavy weights on closely separated exemplars of different classes and heavy losses on well separated exemplars that belong to the same class are developed and a linear transformation is developed to minimize such a loss function. It is shown in [1] that a global minimum loss solution can be achieved using convex optimization. LMNN attempts to pull, through linear transformation, exemplars of similar class and push those of different classes [1]. The reader is referred to [1,2] for details on this approach. The LMNN code used in this paper was downloaded from [5].

2.4 Maximum Correlation
This is a classifier where the chosen class is based on maximizing the cross correlation between the signature of the unknown target and that of the known targets at all known azimuth positions.

$$r = \max \{ \max_k \{ corr(X, C_{k,\theta}) \} \}$$

The maximum of each cross-correlation between the unknown and the catalogue is found and then the class with the largest maximum correlation is selected. This classifier is used here for comparison purposes.
3. SIMULATIONS AND DATA USED

3.1 Data Used

To assess the performance of the proposed system, real radar returns of models of commercial aircraft, Boeing 707, 727, 737, and DC10 as recorded in an anechoic chamber are used. It is assumed that the receiver records the target backscatter at a certain azimuth position. Data corresponding to aspect angles of 0, 10, and 20 degrees were used in this case. The data was obtained in a compact range at very high signal-to-noise ratio using a stepped-frequency radar in the 2-12 GHz range with a 50MHz step. To estimate classification error, independent Gaussian noise was added to the real and imaginary components of the data each with a variance of 0.5 the additive noise power. To assess the performance of each classification system the error rate is plotted versus signal-to-noise ratio.

Figures 1, 2, and 3 show a comparison between nearest neighbor, maximum correlation, and LMNN assuming complete unknown target azimuth knowledge a priori. Figure 1 shows that both LMNN and nearest neighbor perform equally well while the correlation approach lags behind. Figure 2 shows the importance of knowing the target zero-time reference in advance. Both LMNN and nearest neighbor cannot recognize unknown targets while the correlation approach (which is shift invariant) can. Figure 3 shows that the nearest neighbor and correlation approach collapse in the presence of extraneous scatterers while the LMNN maintain reasonable recognition performance levels.

Figures 4, 5, 6, 7, and 8 assume partial knowledge of the target azimuth within 20 degrees uncertainty cone. Figure 4 shows that under additive white Gaussian noise assumption, the nearest neighbor (though not optimal) performs fairly reliably and better than LMNN. This could be due to the limited number of classes (four possible classes in this case). Figure 5 shows a similar performance pattern when the additive noise is correlated (generated using an auto-regressive single pole filter). Figure 6 shows the power of LMNN when extraneous scatterers are contaminating and altering the unknown target signature. Figure 7 shows another scenario where LMNN and the nearest neighbor technique perform equally well when only the magnitude of the return is used for classification, and Figure 8 shows that LMNN performs slightly better than nearest neighbor when the recognition system is misinformed about the unknown target azimuth by an error of 10 degrees.

These results show that, although the nearest neighbor technique is a powerful classification system in many scenarios, it performs poorly when the target azimuth is mismatched, phase information is lost, or when extraneous scatterers are included in the backscatter. Both nearest neighbor and LMNN cannot recognize targets if the zero-time reference is unknown, and the correlation classifier is more appropriate. So, among distance based techniques, LMNN seems appropriate in scenarios where extraneous scatterers are present and it seems that the LMNN algorithm finds class separation solutions that minimize the impact of extraneous scatterers.

4. CONCLUSIONS

Radar target classification using distance and correlation-based methods were investigated using real model aircraft backscatter. The simulation results show that large margin nearest neighbor techniques developed in [1,2] has potential in scenarios where extraneous scatterers are present or when the classifier is misinformed about target azimuth. Both distance-based techniques (nearest neighbor and LMNN) cannot recognize unknown targets where the zero-time reference is unknown. In scenarios where the noise additive Gaussian (correlated or not), the nearest neighbor (given its simplicity) is an attractive classification technique even when the target azimuth is completely known or partially known to be within a prescribed range.
Figure 1. Comparison between classification techniques assuming complete azimuth knowledge and additive white noise.

Figure 2. Similar scenario as in Figure 1 but assuming the unknown target signature has a random phase shift.
Figure 3. Similar scenario as in Figure 1 but assuming the presence of 20 extraneous scatterers

Figure 4. Comparison between nearest neighbor and LMNN assuming partial azimuth knowledge and additive white noise.
Figure 5. Comparison between nearest neighbor and LMNN assuming additive correlated noise.

Figure 6. Comparison between nearest neighbor and LMNN assuming extraneous scatterers.
Figure 7. Comparison between nearest neighbor and LMNN assuming classifier uses only magnitude of backscatter.

Figure 8. Comparison between nearest neighbor and LMNN assuming classifier is misinformed about target azimuth by 10 degrees.
REFERENCES