

Multi-Perspective Radar Target Classification

M. Vespe, C. Baker, and H. D. Griffiths
University College London
Dept. Electronic and Electrical Engineering
Torrington Place, London WC1E 7JE, UK

Abstract

In this Paper we present a novel multi-perspective approach to radar target classification aimed at enhancing performance compared with that of traditional classifiers. A network of geographically separated radar systems is used to provide the multiplicity of perspectives. Data types that provide the input for the classification process include; high range resolution (HRR) profiles and Doppler processed ISAR imagery. The multi-perspective approach also enables tomographic three-dimensional image reconstruction. The potential improvement in classification performance offered by these two forms of processing is discussed.

Keywords: HRR profiles, ISAR, multi-perspective classification, netted radar, netted sensing

Introduction

The ability to reliably detect and classify targets using radar has many important applications for both civil and military systems. Investigations into radar target classification have been fuelled over many years by the progressive increase in the amount and quality of information available from advanced radar systems. Chief amongst these improvements is the development of very high range resolutions that provide a detailed signature of the target to be classified. However, as the electromagnetic backscatter behaviour of complex targets is extremely sensitive to radar parameters, orientation and environment traditional classification techniques based on a single view of the target only provide a limited level of performance. This is often insufficient for many applications. A network of radar offers a way of collecting backscattered radiation with higher information content from the target than is possible using a single monostatic radar. Furthermore, as it shown in Baker and Hume (1), the possible

employment of both monostatic and bistatic radars might provide a valuable counter to stealth technology which has been largely aimed at defeating monostatic radar only. This study on potential improvements in target classification using multi-perspective views of targets is at an early stage but plans have been formulated to develop Automatic Target Recognition (ATR) for a network of radar systems. Although the concept of netting radar systems is not new it is only recent developments in low cost COTS technologies and high speed digital signal processing that are enabling these advanced and complex concepts to be realized.

This paper firstly considers the location of targets by a network of ground-based radar systems. The problem is introduced and solved for a simple two-dimensional scenario. This is followed by an overview of the methods for achieving High Resolution Radar (HRR) profiles and ISAR as this provides the source of data for the classifier. The classification problem is examined and the performance

requirements necessary outlined. This sets the scene for a multi-perspective approach to this problem. Finally possible route to three-dimensional tomographic image reconstruction is also introduced and the options for classification discussed.

Network of Radar and Location

In this section radar networks are introduced and used to examine target location. This has a number of characteristics that may be exploited in classification.

In figure 1, a two-dimensional scenario is shown. In this case, at least two monostatic radars are necessary to solve the problem of location of a single moving target. After calculating the two ranges R_1 and R_2 , knowing the position where they intersect, the system is able to calculate the position of the target with respect to the global coordinate system. As it explained in Sauer et al (2), this procedure is known as multi-lateration.

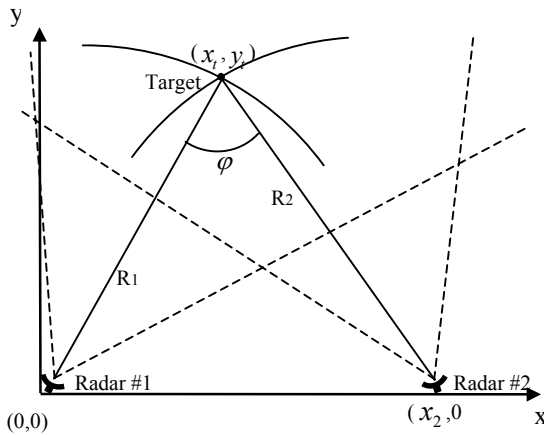


Figure 1: Two-dimensional scenario.

By resolving the geometry the target coordinates are given by [1]:

$$x_t = \frac{R_1^2 - R_2^2}{2x_2} + \frac{x_2}{2} \quad (1a)$$

$$y_t = \sqrt{R_2^2 - \left(\frac{R_1^2 - R_2^2}{2x_2} - \frac{x_2}{2} \right)^2} \quad (1b)$$

Clearly performance is a function of signal to noise ratio, beamwidth and range and can be further enhanced by ISAR imaging of moving targets. A useful parameter for the classification task is the angle φ between the two lines of sight from the target to the radars:

$$\varphi = \arctg \left(\frac{y_t x_2}{y_t^2 + x_t(x_t - x_2)} \right) \quad (2)$$

As will be seen later, this angle expresses the relationship between the perspectives under which each node of the network sees a target.

As well as solving location problems, it's possible to deduce the speed vector of the target with respect to the global coordinate system by processing the two relative velocities obtained by the individual radar systems. Knowledge of the motion parameters of the target is necessary to avoid blurring in the ISAR imagery caused by phase errors introduced by translational and other motion.

HRR Profiles and ISAR Imaging

A radar target may be classified by exploiting its backscattered information. This is usually expressed either by the Radar Cross Section (RCS), HRR profiles or Doppler imagery. These parameters are related to each other and describe the electromagnetic scattering behavior. RCS is a single value representing the total backscattering. The HRR profile is a one-dimensional image comprising multiple resolution cells. An ISAR image is a two-dimension high resolution representation of target back scatter. ISAR offers the most detailed description of a targets scattering characteristics and is expected to be the

richest source of information for classification. However, it also suffers from the strictest requirements to correctly form imagery, so here we consider both HRR profiling and ISAR.

To achieve high range resolution a frequency modulated stepped-frequency waveform is employed. This reduces the instantaneous bandwidth requirement while increasing the overall bandwidth. HRR range profiles and ISAR images are both produced by processing a wideband reconstruction of the target reflectivity spectrum. By placing side by side N narrower chirp waveforms of bandwidth B and an inter-pulse frequency step also equal to B , it is possible to synthesize a total bandwidth of $B_t = B \cdot N$, [M]. This is illustrated in figure 2.

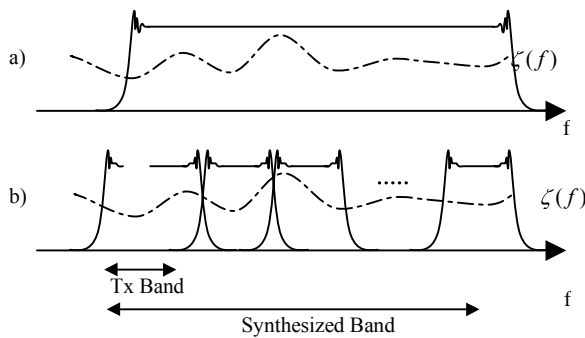


Figure 2: Spectrum reconstruction of the target reflectivity function by one single chirp pulse (a) and by stepped-frequency coherent addition of sub-spectra (b).

A range profile is defined as a time sequence of the vector sum of signals reflected back by different scatterers within a range cell. By matched filtering the stepped frequency waveform a range resolution $R_{res} = c/2NB$ is achieved. The received signal is the transmitted pulse modulated by the corresponding sub-spectrum representing the target reflectivity function. By adding the compressed

individual portions of reflectivity function $\zeta(f)$, which result from time convolution between each received pulse with the complex conjugate of the corresponding transmitted pulse, the entire spectrum is eventually obtained commensurate with the extended bandwidth.

The HRR profile may then be synthesized from an inverse FFT applied to each row of the time history of the target's frequency domain signature matrix. This is demonstrated in figure 3. As explained in Wehner (4), to obtain the magnitude of the ISAR image's pixel in l -th range cell and j -th Doppler cell ($D_{l,j}$) an FFT is applied to each column of the matrix representing the time history of target's range profile.

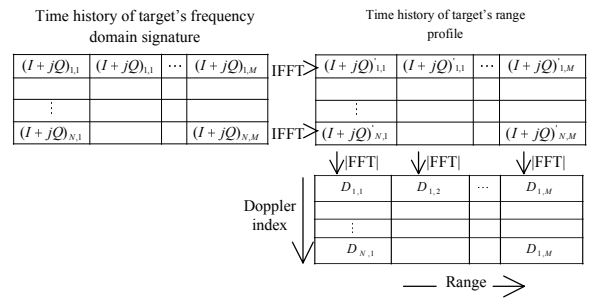


Figure 3: Matrix decomposition for HRR profiles and ISAR imagery.

Slant range resolution of both the HRR profiles and the ISAR imagery is strictly related to the bandwidth of the synthesized spectrum:

$$\Delta r_s = \frac{c}{2NB} \quad (3)$$

For HRR profiles the resolution achieved in cross-range depends upon the illuminating beamwidth and is normally treated as a one-dimensional image. For ISAR the resolution achieved in cross-range depends upon the minimum resolvable frequency Δf_D between two adjacent scatterers. Doppler resolution is also related to the

available coherent time of integration T which is equal to the time required to collect the N chirp returns. Therefore, consecutive reflectivity samples from the same range cells are taken every $N\Delta t$ seconds [D]:

$$\Delta f_D = 1/N\Delta t \approx 1/T \quad (4)$$

As a consequence, the cross-range resolution can be written as:

$$\Delta r_c = c\Delta f_D / (2\omega_0 f_c) = \lambda / (2\omega_0 T) \quad (5)$$

where $\lambda = c/f_c$ is the illuminating wavelength and ω_0 is the angular velocity of the target rotational motion.

In ISAR image processing the motion of the target is an unknown. The target motion can be seen as the superposition of rotational and translational motions with respect to each radar system of the network. As shown in equation 5, if the former contributes to the ability to resolve in cross-range, in order to obtain a focused image of the target it is necessary to compensate for phase errors due to the translational motion occurring during data collection. This is usually referred to as motion compensation. After this correction an ISAR image may be obtained by processing data collected over an arc of circular aperture whose dimensions depend on the rotational speed of the target ω_0 and the integration time T . There may still be further residual motions that require correction using autofocus techniques.

Classification

The ability to determine a particular class to which a target belongs among the many possible classes is known as target classification. Target classification generally requires a greater signal to noise ratio than target detection. The many small scatterers comprising a target might be

more important for classification than the few large scatterers that are more important for detection. Furthermore, the ability to perform non-cooperative target classification depends on the amount of information collected and processed by the system.

There are two main aspects to target classification. The first is to isolate the target returns from the clutter echoes (e.g. by filtering) and to extract the features that can help distinguish the class of the target. The second aspect is related to the method used for performing the decision as to which class or target type the feature data belongs. When target classification is achieved through automatic computation it is usually referred to as Automatic Target Recognition (ATR)

In ATR the classification task requires complex techniques and there are a number of approaches that can be used []. For example in a model based technique a model of the target is made by CAD and Electro-Magnetic simulations. This enables many simulated versions to be compared with the target signature to be classified. This is a computationally intensive technique. Alternatively, in a template matching based technique many real versions of the target signatures (at a large number of geometries) are stored in a database and subsequently compared with the target detected in order to assign it to a class. Consequently a very large database is needed. Further if the target is altered in some way (e.g. a tank may carry some additional equipment) then the templates may no longer represent the modified signature and the classification can fail. Finally, pattern based techniques exploit features extracted from the input signature. These might include peak amplitudes and their locations in a HRR profile or ISAR image. These then are used to make a multi-dimensional feature vector which can be compared with the stored feature vectors

from previous measurements of known targets in order to perform classification. This technique is less costly in terms of computation and it is consistent with a netted radar framework as a number of perspectives of the same object are available.

Classification typically requires a high probability of declaration P_{dec} which is the probability that a detected target will be classified either correctly or incorrectly as a member of the template training set. A target is known when its feature-vector belongs to the training data set. A second performance requirement is to have a high probability of correct classification P_{cc} . According to Mitchell and Westerkamp (5), these two parameters are often related each other: if P_{dec} is low, the ATR system may declare just those cases of very high certainty of correct classification. As a result, the system is able to achieve a very high P_{cc} but may not classify all possible targets. Finally, a low probability of incorrectly classifying unknown targets P_{fa} is required, i.e. a low probability that unknown target is incorrectly classified as a different object in the ATR database. This final task is particularly difficult since it is impossible to include a specific class of unknown targets in the template. This is because there is always a possibility that the classifier would need more information to make a correct decision [A].

The decision, which is usually made automatically, may be performed with two different data input types. The first is one-dimensional target classification by HRR profiles. The HRR profile can be thought of as representing the projection of the apparent target scattering centers onto the range axis. Hence the HRR profile is a one-dimensional feature vector. The second data input is the two-dimensional ISAR image. This perhaps lends itself to being processed by standard classifying procedures such as

the method of moments, classification of scattering centers or the projection classification where the projection of the pixels intensities are expressed as a combination of two orthogonal vectors to make a two-dimensional feature.

From Novak (6), where a one-dimensional and a two-dimensional classification algorithm is compared, the best performance in terms of P_{cc} was obtained using an ISAR image matching classifier. This might be expected as we have more pixels of information describing the target signature. It is also noted, however, that the processing time is greater.

3-D Imaging

A network of radars enables multiple perspective imagery of a target to be obtained. Additionally, this allows tomographic three-dimensional reconstruction of the target reflectivity function.. If we consider the geometry shown in figure 4, where the radar is located in the origin of a coordinate system whose axis x coincides with the line of sight between the radar and the reference center of a scatterer (y_0, z_0) . As in Genyuan et al (7), defining ω_y and ω_z as the two components of the rotational motion usable for resolving in Doppler frequencies, then:

$$\omega_0 T = T \sqrt{\omega_y^2 + \omega_z^2} \quad (6)$$

From equation 5, we can write the two components of resolution:

$$\Delta r_y = \lambda / (2\omega_y T) \quad (7a)$$

$$\Delta r_z = \lambda / (2\omega_z T) \quad (7b)$$

If we consider a point scatterer P , its image location in the image will be defined by the range cell and the Doppler frequency:

$$f_p = \frac{1}{\Delta r_y}(y_p - y_0) + \frac{1}{\Delta r_z}(z_p - z_0) \quad (8)$$

The imagine plane is determined by the x axis and the point scatterers which lie the line made up by:

$$y_p \Delta r_y = z_p \Delta r_z \quad (9)$$

In a netted radar framework we have a number of projection planes equal to the number of radars. These planes are combination of different lines of sight and, consequently, they produce multiperspective views of the target. By knowing the angle φ between the lines of sight of the netted radars it is possible to process the images in order to form a single three-dimensional image of the target.

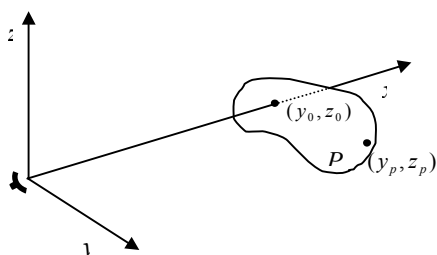


Figure 4: Geometry of a generic target rotating around the point (y_0, z_0) .

Multi-perspective Classification

Traditional classification procedures, that normally process a time sequence of returns collected from a single aspect of the target, are often characterized by poor performance. Because of their crucial fields of application (both military and civilian), a higher confidence of correct classification is required. Networks of co-operating radar systems offer a possible solution for improving classification performance as a consequence of the richer data set that can be gleaned from multiple perspectives. With more perspectives, an approaching target is seen from different directions. As a consequence, the target's reflectivity function can be extended over the

monostatic case to include a spatial dimension. i.e. the reflectivity function is made up of a number of spatially distributed samples. This is illustrated in figure 5. In this way the more information is being input to make the classification decision.

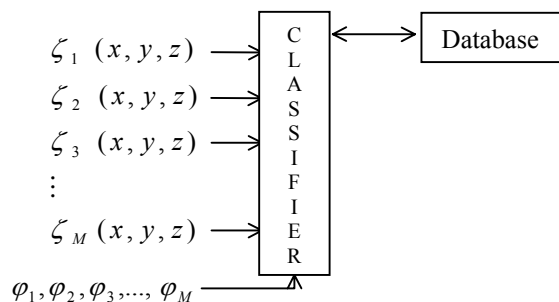


Figure 5: multiperspective classifier. Reflectivity function samples are collected from different views of the target.

There are a number of ways in which the network configuration can be exploited. The simplest is to treat the individual radar systems as independent and we simply have a number of reflectivity functions to attempt classification rather than the simple one provided by the monostatic case. Alternatively every radar station could co-operate with the others during the data collection phase.

If collected coherently the data be may re-assembled using the principles of tomography to provide a more complete (single) three-dimensional image. This has a higher level of information content (although ambiguities may be present) and hence has the potential for better classification if the image can be correctly formed. The multi-perspective classifiers (figure 5) may use other information such as the angle φ between the lines of sight. This parameter allows the classifier to optimize the matching algorithm used, avoiding to compare the current feature-vector with all the database for each node of the network, focusing the attention on groups of M (as the number of nodes in

the network) vectors spaced by the opening angles φ_i .

Conclusion and future works

The potential for classification enhancements due to a multiperspective collection of reflectivity data in a netted framework has been introduced. A number of approaches are possible. A tool to process multi-perspective data and compare differing techniques will be developed. Furthermore, a multiperspective classifier and its performance will be investigated to determine the improvements using monostatic radar data only.

Acknowledgements

This work has been sponsored by the EMRS Defence Technology Centre. The authors acknowledge the support of Thales Sensors for providing ADAS files from real targets.

References

1. Baker, C.J., and Hume, A.L., 2003, IEEE AES Magazine, 18, Issue: 2, 3-6
2. Sauer, Th., Bethke, K. H., Buettner, F., Roede, B., and Schroth, A., 1997, IEEE NR Conf., 19-24
3. Wilkinson, A.J., Lord, R.T., and Inggs M.R., 1998, IEEE Proc. CONFIG '98, 101-104
4. Wehner, D.R., 1995, "High Resolution Radar", Artech House, Norwood, USA
5. Mitchell, R.A., and Westerkamp, J.J., 1999, IEEE Trans. AES, 35, 1077-1094
6. Novak, L.M., 1991, IEEE Int. Conf SE, 6-12
7. Genyuan, Wang, Xiang-Gen Xi, and Chen, V.C., 2001, IEEE Trans. IP, 10, 436-447