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Singular Value Decomposition applied to automatic target recognition with high resolution range profiles

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Abstract: Target recognition based on radar signatures such as high resolution range profiles is a key research domain in the Defense industry. This paper presents an automatic target recognition method based on the application of Singular Value Decomposition to a matrix of range profiles in order to reduce dimensionality, extract the main features and apply recognition in the transformed domain. So as to confirm the feasibility of the methodology, identification experiments of real in-flight targets against a database of simulated aircraft are conducted. Results show good average recognition rates implying SVD is a proper tool for recognition experiments.

Keywords: NCTI; Target recognition; SVD; HRRP; synthetic database; actual measurements

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1. Introduction

Radar systems are key components in military and civilian schemes and with the development of wideband radars new applications have emerged related to this kind of sensor. That is the case of automatic target recognition based on radar imagery, where radar is used to identify an unknown target. In order to achieve that, no communication with the target is established but recognition relies on the comparison of its sensed radar signature with a reference database. In this paper a target recognition methodology based on one dimensional high resolution radar imagery is presented. 1D radar images present the scatterers of a moving target projected onto the dimension of the radar line of sight (LOS) and they are known as high resolution range profiles (HRRP). Profiles are composed of range bins and contain the distribution of the scattering centers of a target providing information about its structure [1]. Target recognition based on HRRP has been a key research domain in the last decades due to the fast and easy collection and processing of profiles [2, 3]. Traditionally, target recognition based on HRRP was accomplished through comparison between profiles coming from actual measurements of in-flight targets [4], or on the contrary, through comparison between profiles coming from electromagnetic simulations [5]. Since in those studies identification is carried out with measurements in the same domain, that is to say, actual measurements vs. actual measurements, or simulated measurements vs. simulated measurements, the classification performance of these algorithms is not easy to determine due to their poor generalization ability. The purpose of an identification system is the recognition of a real target through comparison with a wide database of targets. Thus, this database should be populated with measurements of all existing aircraft in as many trajectories as possible; this means that the database should have the generalization capability. In order to obtain this wide database, its population with HRRP simulations is thought to be a good choice since any existing aircraft could have been previously simulated in any trajectory and configuration. According to this, in this paper identification of actual HRRPs is carried out by comparison with a database of simulated HRRPs. Simulated HRRPs have a very clean signature while actual HRRPs suffer from noise and other unwanted effects making the recognition process an arduous task. In order to overcome these differences between simulated and actual profiles, Singular Value Decomposition (SVD) [6] is applied to matrices of HRRP. By doing so, the possibility to work in a transformed domain where dimensionality can be reduced so as to extract the main features and reduce the unwanted information is provided, and also the computational burden is lightened, which has been found to be high in cases where recognition is accomplished using 2D radar imagery and algorithms based on correlation [7].

This paper is organized as follows. Section 2 explains the SVD technique and the definition of the proposed algorithm. Section 3 provides a discussion of the results obtained and finally, Section 4 presents the conclusions and further research purposes.

2. Identification Methodology

2.1. Singular Value Decomposition

SVD is a robust tool that can be used to decompose any matrix into orthogonal basis spaces [6]. With SVD it is possible to find the best approximation of the original data points using fewer dimensions. Hence, SVD can be seen as a method for data reduction. If $X \in \Re^{N \times M}$ is a matrix of real HRRP (assuming $N>M$), with M being the total number of profiles and N the number of range bins, then, this rectangular matrix X can be decomposed into the product of three matrices:

$$X = USV^T \qquad (1)$$

where the columns of $U \in \Re^{N \times N}$ are the orthonormal eigenvectors of XX^T, namely the ith left singular vectors of X; the columns of $V \in \Re^{M \times M}$ are the orthonormal eigenvectors of $X^T X$, namely the ith right singular vectors of X; and $S \in \Re^{N \times M}$ is a diagonal matrix containing the p singular vectors of X in descending order $S = diag(\sigma_1, ..., \sigma_p)$ with $p = \min\{N, M\}$. Larger singular values imply larger contribution of the corresponding singular vector in forming the target signal. The Eckhart and Young theorem [6] states that the top singular vectors with the associated highest singular values provide the best approximation of the data. Thus, by applying SVD to the HRRP matrices and selecting the most significant singular vectors, the N-dimensional vector space (when referring to matrix U¸ or M-dimensional when referring to V) can be split into a signal and a noise subspace.

2.2. Algorithm definition

The left singular vectors, u_i, span the range domain basis space while the right singular vectors, v_i, span the angle domain basis space. Since HRRPs present the target reflectivity into the range domain, in this study only the left singular vectors will be used in the identification process. Taking into account the weights of the singular values, σ_i, and setting an energy threshold η as in (2), the *signal subspace* is defined as the K largest left singular vectors, u_i, while the *noise subspace* is discarded resulting in a dimensionality reduction.

$$\frac{\sum_{i=1}^{K} \sigma_i}{\sum_{i=1}^{p} \sigma_i} = \eta \tag{2}$$

In this paper we call test set to the profiles to be identified and training set to the data that populate the database of already known targets. After alignment and normalization of both sets of range profiles, SVD is applied. Let X^R be the *signal subspace* containing the K largest singular vectors of the measurement to be identified, and let u_i^s be the ith left singular vectors obtained after SVD decomposing a matrix of profiles in the training set corresponding to target s. The identification process is based on finding the target s that minimizes the angle between the projection of its left singular vectors u_i^s onto the *signal subspace* of the test sample, X^R. As noted, the weight of the singular values sets the importance of the singular vectors in the formation of a target signal, thus, the angle between each u_i^s and the signal subspace should be also weighted. The metric proposed in (3) returns the accumulated weighted angle between the *signal subspace* of the test matrix and the singular vectors of each aircraft s in the training set.

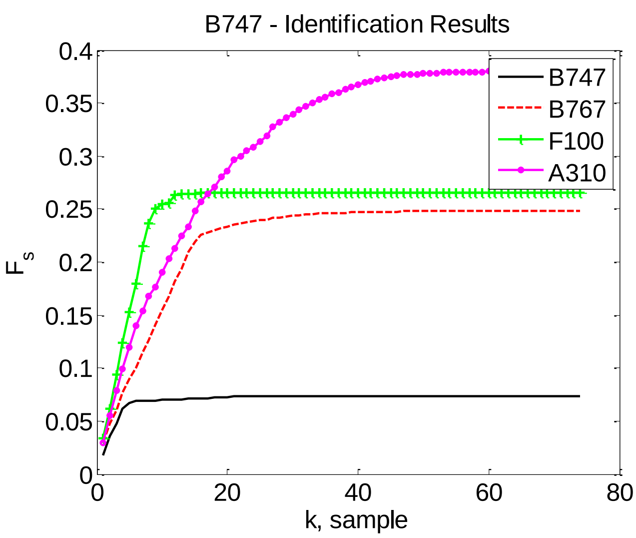
$$F_s(k) = \frac{1}{\sum_{j=1}^{K} \sigma_j^s} \sum_{i=1}^{k} \sigma_i^s \cdot \angle(X^R, u_i^s) \quad ; \quad k=1,...,K \tag{3}$$

In (3), $\sigma_{i,j}^s$ are the K first singular values associated to each aircraft in the training set and $\angle(X^R, u_i^s)$ is the angle between the test set *signal subspace* and the ith singular vector of the training set as defined in [6]. The algorithm decides the test sample X belongs to the target that minimizes the final value of F_s.

3. Results

In order to prove the validity of the algorithm proposed in this paper and since the generalization capability is sought, the training set, namely the aircraft database, is populated with synthetic HRRP of aircraft models simulated in an ideal environment using the RCS-prediction code FASCRO [8]. The test set comprises measured HRRP from a civil aircraft measurement campaign [9], where data were collected with the FELSTAR S-Band radar at TNO-FEL in The Netherlands. As noted, experiments will compare actual measurements vs. simulated ones. The test set comprises measurements of 4 different civil in-flight aircraft in different flighpaths, the Boeing B747-400, the Boeing B767-300, the Airbus A310 and the Fokker100. On the other hand, for the population of the training set the CAD models of those aircraft have been developed at INTA (National Institute for Aerospace Technology, Spain) and their profiles have been predicted by FASCRO using the information of the estimated aspect angles given in the test set. It must be noted that the training set has been developed considering every aircraft as perfect electric conductors (PEC) with no protruding elements and that FASCRO, as it uses high frequency techniques, does not take into account all EM effects when predicting RCS. Hence, noticeable difference between test and training sets is expected hindering the identification process. A total number of 35 legs are classified. Each leg (sequence of collected profiles ordered in time) consists of 100 up to 300 normalized and aligned profiles. Most studies tend to classify one profile at a time. Here, the identification is carried out using a sequence of consecutive profiles so as to have more information about the position of the scattering centers of the target and their evolution along its trajectory. After alignment and normalization of profiles, SVD is applied to both sets. Setting the energy threshold η as in (2), the *signal subspace* is defined as the K most significant left singular vectors, and F_s is obtained for each synthetic aircraft s in the training set. Finally, the algorithm decides the test set belongs to the aircraft type s which minimizes F_s. Fig. 1 shows an example of the curves obtained in the identification of a measurement of a B747. As seen, the curves have a monotonically increasing tendency, however, they eventually reach a point of saturation where the synthetic singular vector u_i^s, due to its corresponding singular value, does not add almost any new information to the recognition process.

Figure 1. Identification results for a test sample of a B747.



In the example of Fig. 1 the threshold is set to η = 0.9 resulting in K = 74 singular vectors that define the signal subspace for that measurement. Table 1 shows the complete confusion matrix obtained for the classification of all the aircraft in the test set with a threshold of η = 0.9.

Table 1. Confusion matrix of the test set classification using F_S.

Class	B747	B767	A310	F100	Error(%)
B747	9	1	0	0	10.0
B767	0	7	1	2	30.0
A310	0	0	8	0	0.0
F100	1	0	0	6	14.3
TOTAL					**14.3**

The error rates found for this experiment show a total error rate of 14.3%, that is to say, an overall success rate of 85.7%. As stated, actual profiles suffer from noise, clutter and other unwanted information while synthetic ones are run in ideal scenarios without consideration of all propagation effects and with CAD models that are approximations of real aircraft. Despite these obstacles, it can be stated that recognition is accomplished with a good success rate in contrast to other methods such as the one presented in [10], where recognition of actual profiles with synthetic ones is achieved with an error rate of 35.5%.

4. Conclusions

In this paper a methodology for automatic target recognition based on Singular Value Decomposition is shown. As noted, the main drawback of using synthetic profiles as database for the recognition is the dissimilarity between actual measurements and simulated ones. However, the application of SVD helps to overcome these differences since not only the reduction of the amount of data is achieved due to the discarding of the *noise subspace*, but also the possibility to work in a transformed domain is accomplished implying less computational burden. Considering the dissimilarities in the profiles, the metric proposed in this paper based on the angle between *signal subspaces* with a weighting element achieves good identification results. However, in order to improve the success rate and validate the algorithm, further experiments should be carried out with a wider database and applying additional preprocessing algorithms to the profiles, such as Power Transformation.

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Author Contributions

The main contributions of this study not only include the identification of actual data coming from in-flight targets by comparison with a database of simulated range profiles, but also, on the one hand, the use of SVD in order to discard the noise subspace and to work in the transform domain in the classification process, and on the other hand, the definition of a new metric based on the angle between subspaces with a weighting element.

Conflicts of Interest

The authors declare no conflict of interest.

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