IMPROVED AUTOMATIC TARGET RECOGNITION USING SINGULAR VALUE DECOMPOSITION

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ABSTRACT

A new algorithm is presented for Automatic Target Recognition (ATR) where the templates are obtained via Singular Value Decomposition (SVD) of High Range Resolution (HRR) profiles. SVD analysis of a large class of HRR data reveals that the Range-space eigenvectors corresponding to the largest singular value accounts for more than 90% of target energy. Hence, it is proposed that the Range-space eigen-vectors be used as templates for classification. The effectiveness of data normalization and Gaussianization of profile data for improved classification performance is also studied. With extensive simulation studies it is shown that the proposed Eigen-template based ATR approach provides consistent superior performance with recognition rate reaching 99.5% for the four class XPATCH database.

1. INTRODUCTION

Traditionally, air to ground acquisition of ground target information is categorized into two general areas: Moving Target Indicator (MTI) and Synthetic Aperture Radar (SAR) [1, 2, 5, 9]. MTI has coarse target detection and range determination capabilities. It makes use of target movement for image formation and hence, it is highly effective for distinguishing moving targets from ground clutter. However, a major drawback of the MTI technology is its lack of target recognition capability. On the other hand, SAR's ability to image ground targets with range and cross-range information gives it very good target recognition and identification capabilities, although its tremendous processing requirements prevent it from being used as a wide area surveillance technology [2]. Furthermore, SAR's effectiveness is limited to stationary targets because target movement causes blurring in the cross-range domain making recognition a difficult task.

High Range Resolution (HRR) technology is being developed and promoted by the Model Based Vision Laboratory, Wright-Patt AFB, as a potential target recognition capability that promises to bridge the gap between MTI and SAR. HRR-ATR technology is based on processing the information contained in the range profiles themselves without generating the cross-range information that cause blurring in SAR for moving targets. Hence, the primary advantage of HRR-based ATR is expected to be superior ATR performance for moving targets although at the preliminary stage of this project, the effectiveness of HRR-ATR is being tested for stationary targets, as reported in this paper.

In this work, a new air-to-ground HRR-ATR algorithm is proposed, where the template features are obtained via SVD of HRR training profiles. The SVD operation projects the information content in an HRR profile matrix onto orthogonal basis spaces decoupled in the range and angle domains. Theoretically, the range-space eigenvectors constitute the "optimal" features in the range domain [11]. SVD analysis of a large class of the XPATCH database indicates that over 90% of target energy is accounted for only by the largest singular value. Hence, we propose to use the range-space eigen-vector corresponding to the largest singular value as templates for target classification. Our studies also show that appropriate pre-processing of detected HRR data can be highly effective in improving ATR performance. We investigate the effectiveness of normalization of range profiles as well as Gaussianization using Power Transform (PT) operation [4, 13] in enhancing classification performance. It is demonstrated that for detected-HRR data, Gaussianization using low PT coefficient followed by normalization enable simple matched filtering (MF) to provide excellent classification performance when compared with linear Least-Squares (LS) based classification algorithms. Our studies further indicate that the Eigen-template based approach delivers superior ATR performance when compared with algorithms that use Mean templates [13]. The simulated XPATCH database (unclassified) has been used to conduct all the simulations and for this 4-class database, over 99% ATR efficiency has been achieved using the proposed eigen-template based approach.

2. PRE-PROCESSING OF HRR PROFILES

All results reported in this paper were performed using the XPATCH database containing simulated Complex Phase History (CPH) of four Target classes, M1-Tank (M1), T72-tank (T72), School Bus (SB) and Fire Truck (FT). Figure 1 depicts the process of generating detected HRR profiles (range vs. angle) and SAR data (range vs. cross-range) from the raw CPH (frequency vs. angle). The modules for generating HRR Eigen-Templates are also included. Note that 2D FFT is needed to generate SAR images whereas only 1D FFT is necessary for HRR profiles, with considerable front-end computational savings for the later case.

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2.1. Power Transform operation

As shown in Fig. 1, Detected-HRR data are formed using absolute value of the Complex HRR data. Detected HRR is positive valued and tend to be Rayleigh distributed for which optimum detection and estimation results are not usually straight-forward. On the other hand, many commonly used detection and estimation algorithms possess optimality properties for the Gaussian case [7]. Interestingly, in Pattern Recognition context it has been shown that any distribution can be converted to close to normal by using the following Power Transform (PT) of the data [4],

$$Y = X^v, \qquad (0 < v < 1) \tag{1}$$

where, v denotes the PT-coefficient. It has also been shown in [11] that the Gaussianity property of Y enhances with reduction in the value of the PT-coefficient v. Hence, the HRR training data were tested for Gaussianity in order to determine appropriate value of v so as to achieve improved ATR performance.

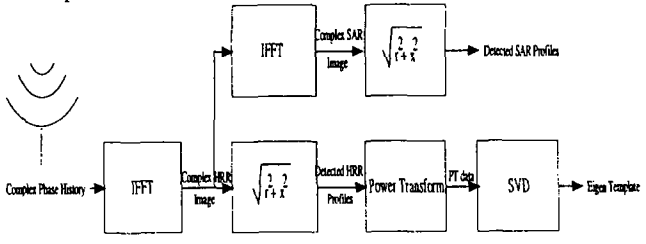

Fig. 1: HRR, SAR and Eigen Template Generation

2.2. Tests for Gaussianity

Two types of Tests were conducted to obtain the optimum value of the PT-coefficient, Chi-square Analysis [3, 6] and Bispectrum Analysis [8]. Chi-Square is a standard test for Gaussianity, whereas the Bispectrum based test exploits an important property of Gaussianly distributed random variables that their third-order moment as well as Bispectrum are theoretically zero [8]. Both tests were conducted for a set of values of v over an ensemble of HRR realizations [13]. The decision whether a realization is gaussian or not was based on some pre-determined thresholds [3, 8]. Both tests indicated that the detected HRR data tend to be *more* Gaussian as the value of v is lowered, as predicted theoretically by Fukunaga. In our Chi-square tests with XPATCH-HRR data, the optimum value of v was found to be 0.08, as depicted by Figure 2. This result was also corroborated by the Bispectrum based test (results not included due to space limitation).

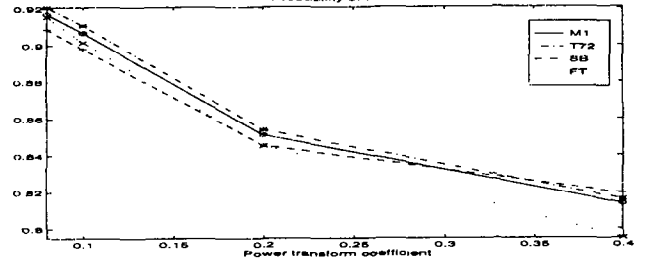

Fig. 2: Probability of passing the Chi-Square test

2.3. Template Normalization

In case of HRR profiles, the crucial information on the differences between various target classes are contained in the respective range profile structures. The relative amplitudes in the range profiles depend on the strengths of the radar returns from the scattering centers and the relative positions of the scattering centers of a particular target. However, the total template energy of one target may be significantly stronger than other classes, due to amplification or attenuation during data collection. In that case, the signal strength (or energy) and not the relative variations in range profile structures may dominate and overwhelm the ATR decision process. Figure 3(a) depicts a possible scenario where unnormalized templates for four target classes are represented by the blobs. The lines connecting the centroids of the blobs to origin represent the energy whereas the blobs themselves and the angles made with the axes signify the variations in scattering returns for different targets. For this assumed but typical scenario, T72 appears to dominate due to its total signal energy whereas the School Bus profile has the least energy. If ATR decision is made by correlating these templates with an observed range profile to look for a maxima (*i.e.*, Match Filtering), T72 will tend to dominate regardless of the actual target producing the observation profile.

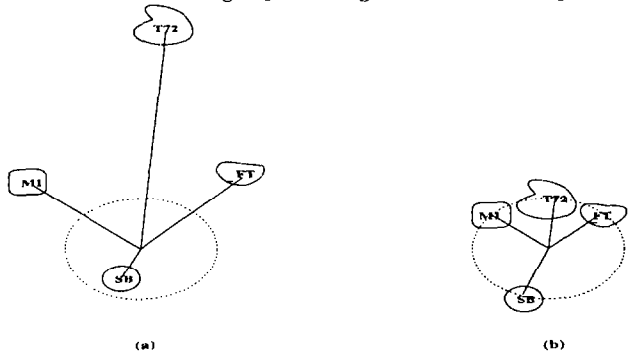

Fig. 3: Effect of Normalization on target recognition, (a) before Normalization (b) after Normalization

The scaling problem depicted in Fig. 3(a) is usually resolved using some form of least-squares (LS) algorithm using a linear model [13]. However, the linear model assumption appears to be ad hoc and is not necessarily unique, depending possibly on data type which in turn may affect classification performance. Instead, we propose to use normalized templates, as depicted by Fig. 3(b), where the template profiles for all targets are normalized to have same length (*i.e.*, energy), while preserving their angular separations and relative variations in scattering returns as represented by the blobs. If an observed profile is to be compared with these templates to make an ATR decision, then simple matched filtering (MF) will be sufficient for the purpose. It may be noted here that normalization of templates can be performed off-line and furthermore, MF requires less on-line processing than LS because no matrix inversion is necessary.

3. MEAN TEMPLATE BASED CLASSIFIER

Currently, one of the most common approaches for HRR Template formation is via averaging of the range profiles

over a section of contiguous aspect angles and these are called Mean-Templates [13]. In this case, Power Transform with PT coefficient $v = 0.2$ had been applied to the detected HRR profiles before forming the mean templates. However, the template vectors for all classes were not normalized to the same length. Since the Mean-Template energies may vary between target classes, ATR decisions are based on a Linear LS fit, with associated drawbacks as discussed in the previous section (see Simulation Section for comparison of results).

4. CLASSIFICATION USING EIGEN-TEMPLATES

Singular Value Decomposition (SVD) is a very effective and robust tool for decomposing any matrix into orthogonal basis spaces [10]. Let $\mathbf{X}$ be an $N \times M$ matrix containing detected range profiles at M angular looks containing N range gates each. The SVD operation would produce a basis decomposition into three matrices,

$$\mathbf{X} \stackrel{\text{SVD}}{\Longrightarrow} \mathbf{U}\Lambda\mathbf{V}^T \quad \text{where,} \tag{2}$$

$$\mathbf{U} \triangleq \text{EV}[\mathbf{X}\mathbf{X}^T] = [\mathbf{u}_1\ \mathbf{u}_2\ \cdots\ \mathbf{u}_N] \in \mathbb{R}^{N\times N} \tag{3}$$

$$\mathbf{V} \triangleq \text{EV}[\mathbf{X}^T\mathbf{X}] = [\mathbf{v}_1\ \mathbf{v}_2\ \cdots\ \mathbf{v}_M] \in \mathbb{R}^{M\times M} \tag{4}$$

$$\Lambda = diag[\lambda_{11}\ \lambda_{22}\ \cdots\ \lambda_{MM}] \in \mathbb{R}^{N\times M} \tag{5}$$

where, EV[·] denotes the operation "Eigenvectors of". For range vs. angle HRR data, the left eigenvectors in $\mathbf{U}$ span the orthogonal basis space in the range domain while the right eigenvectors in $\mathbf{V}$ span the angle space. Λ is a diagonal matrix containing M (or N, depending on which is larger. $N > M$ is assumed here implicitly) Singular Values in decreasing order, $\lambda_{11} \geq \lambda_{22} \geq \cdots \geq \lambda_{MM}$, with λ_{ii} representing the weights associated with the i-th eigenvector. Larger singular values imply significant contribution of that particular eigenvector in forming the target signal. Hence those are denoted as "signal subspace" eigenvectors [12]. Interestingly, the range-space and angle-space eigenvectors appear in *decoupled* form after the SVD transformation is applied to $\mathbf{X}$, as shown in (2). Hence, the primary focus of this work has been to exploit the information contained in the decoupled range basis space vectors in $\mathbf{U}$ to perform ATR.

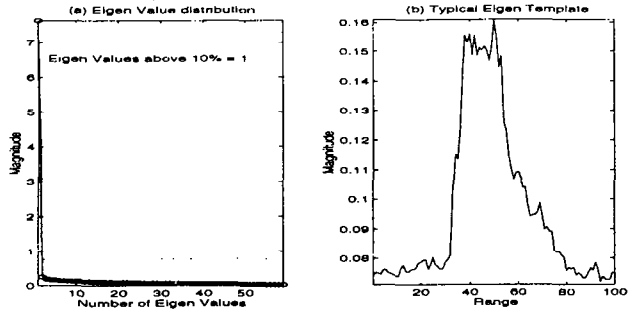

Fig. 4: XPATCH Target T72, $60 - 62.5°$ sector (a) Distribution of Singular Values (b) A Typical Eigen Template

SVD analysis of detected-HRR data for all four classes of the XPATCH database has consistently revealed that *only* 1 out of more than 100 singular values account for more than 90 percent of target energy! This is illustrated in Fig. 4(a) where the singular values of a typical detected HRR data are displayed. The range-space eigenvector ($\mathbf{u}_1$) corresponding to the largest singular value is also plotted in Fig. 4(b). As expected, this vector possesses all the characteristics of a range profile because it happens to be the maximized projection on to the range domain. Hence, we propose to use $\mathbf{u}_1$ of each of the training sectors as templates for performing ATR. This approach of utilizing range-space eigenvectors as templates appears to be new in HRR-ATR.

4.1. Advantages with Eigen-Template based ATR

There are several key advantages in using eigen-templates for classification. First, from minimum Mean-Squared Error context it has been theoretically shown that the eigenvectors of the correlation matrix corresponding to the larger eigenvalues are the *optimal* choice for feature selection [11]. It may be observed from (3) that the range-space (or left) eigen vectors produced by the SVD operation are indeed found from the correlation matrix of the training data. Secondly, Eigen-template formation via SVD involves finding a set of orthonormal basis vectors that best describe the sub-space projection of the target space. The SVD operation in numerically robust and it inherently *decouples* the target basis space (corresponding to the large singular values) from the noise or clutter subspace (corresponding to smaller singular values) [12]. Furthermore, the range-space eigen-vector corresponding to the largest singular value contains the maximum orthogonal projection—information—from the range space of the target-sector under consideration. In addition, range-space eigen-templates produced by the SVD operation for all target classes are automatically normalized to the length of unity, regardless of the signal strength of radar return. Hence, information on the differences between target classes is contained within the amplitude variations in the range profiles.

Another advantage of the normalized eigen-template based approach is that Matched filtering (or location of maximum correlation) gives the optimum result and no on-line least-squares matrix-inverse operation is necessary. It may also be emphasized here that Eigen-templates are formed off-line and no on-line Eigen-decomposition is necessary. In our work with Eigen-template for classification using the XPATCH database, we have observed significant and consistent improvement in classification performance when compared with ATR using Mean-templates. The results are summarized in the next section.

5. SIMULATION RESULTS

5.1. Template and Test Data Generation

The four target XPATCH database contains simulated radar returns at 100 frequencies per look-angle with angular resolution between adjacent looks being $0.04°$. Hence, encompassing the entire $360°$ of look angles, the XPATCH generated CPH matrices are of size 100×9000 for each target. As shown in Fig. 1, HRR data (range vs. angle) is formed by performing 1D FFT in the frequency domain to generate the range information. This is done for each of the look angles followed by the absolute value and PT operations to form the detected-HRR matrix, also of size 100×9000. Templates are formed out of each $2.5°$ sector. However, for this simulated ATR run, the test (or

observation) profiles are formed by taking every 20th profile (starting from 1st and then 21st, 41st and so on) out of the 100 × 9000 detected HRR matrix. Hence, there are 425 test profiles. The remaining matrix is broken down into 144 sectors where each sector (representing approximately 2.5°) is of the size 100 × 59. Hence, in our simulations for a particular PT coefficient v, the templates are formed using these 144 sectors and the ATR tests are conducted using all of the 425 test profiles.

Mean template for each sector is generated simply by averaging the 59 range profiles in that sector to form a 100×1 template profile vector. The eigen-template for the corresponding sector is formed by performing SVD of the 100×59 sector matrix and then the left eigenvector corresponding to the largest singular value is used as the eigen-template for that sector. Note that eigen-templates are unit norm whereas the mean-templates have to be normalized.

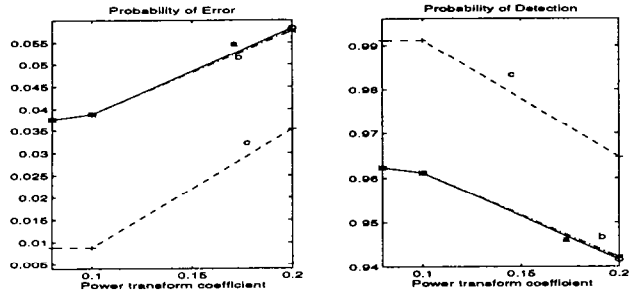

Fig. 5: P_e and P_D using Mean Templates. (a) LS without Normalization and (b) with Normalization. (c) MF with Normalization. $v = 0.08$, 0.1 and 0.2, for all cases.

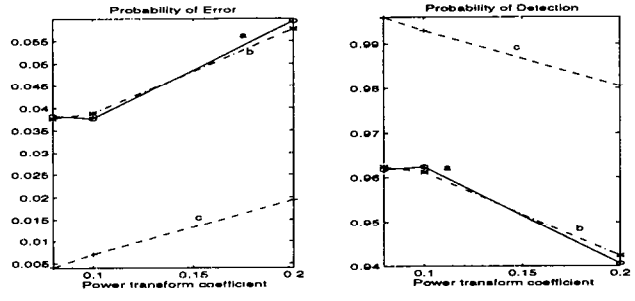

Fig. 6: P_e and P_D using Eigen Templates. (a) LS without Normalization and (b) with Normalization. (c) MF with Normalization. $v = 0.08$, 0.1 and 0.2, for all cases.

5.2. ATR Performance Comparison

Fig. 5 shows the ATR results using Mean templates in terms of Probability of Error (P_e) and Probability of Detection (P_D). The plots marked by (a) and (b) show the results without and with template normalization, respectively, using Least-Squares. Clearly, if LS is used normalization has very little effect. However, if Matched Filtering is used with normalized mean templates, the results improve significantly as shown by Fig. 5(c). Fig. 6 shows the corresponding results using Eigen Templates. Once again, LS performs (plots a and b) poorly regardless of normalization, whereas performance with MF (plot-c) is superior with normalized templates. Both Figs. 5 and 6 demonstrate that ATR performance improves (*i.e.*, P_e reduces and P_D increases) as the PT coefficient is reduced. It may be noted that Matched Filter performs quite poorly without normalization for both Mean and Eigen templates and hence, those results are not included here. According to Figs. 5 and 6, the best results using Eigen and Mean templates are the ones marked as (c) which use Matched filtering with normalized templates. In Fig 7, these two cases are compared separately to show that the performance of the eigen-based approach is superior than that of the Mean-based technique.

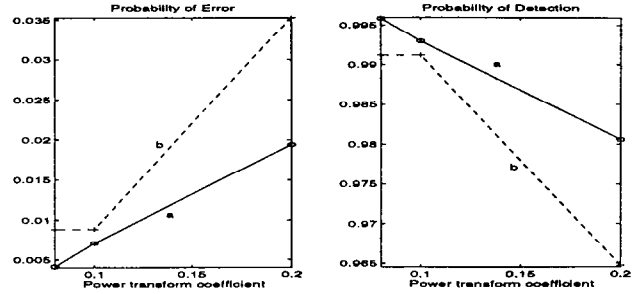

Fig. 7: Comparison of Performance using Matched Filter using (a) Eigen and (b) Mean templates.

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