Improved HRR-ATR using Hybridization of HMM and Eigen-Template-Matched Filtering

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ABSTRACT

In this paper, a new 1-D hybrid Automatic Target Recognition (ATR) algorithm is developed for High Range Resolution (HRR) profiles. The proposed hybrid algorithm combines Eigen-Template based Matched Filtering (ETMF) and Hidden Markov modeling (HMM) techniques to achieve superior HRR-ATR performance. In the algorithm, each HRR test profile is first scored by ETMF which is then followed by independent HMM scoring. The first ETMF scoring step produces a limited number of "most likely" models that are target and aspect dependent. These reduced number of models are then used for improved HMM scoring in the second step. Finally, the individual scores of ETMF and HMM are combined using Maximal Ratio Combining to render a classification decision. The results demonstrate that the hybridization technique achieves improved recognition performance when compared to the independent performances of either ETMF or HMM.

I. INTRODUCTION

The objective of Automatic Target recognition (ATR) is to correctly identify an unknown target from sensed signature. The need for this technology is evident from the numerous "friendly fire" incidents that have occurred in the past several years.

Many ATR systems match the received signature against a set of known target templates to obtain the maximum correlation. Template based ATR provides encouraging result as demonstrated in the work of Novak et al. [1] and many others on SAR images. However, in case of moving targets, SAR images are prone to blurring in the cross-range, causing degradation in target detection performance. For the same reason, Tracking of moving targets is also better suited with HRR profiles than using SAR images. Furthermore, there can be considerable savings in front-end processing because HRR profile generation requires 1-D FFT operation as opposed to SAR's use of 2-D FFT. Hence, one of the dominant trends in ATR research has been to identify ground military targets based on HRR profiles.

The HRR sensor collapses three-dimensional information into a single dimension, making HRR-ATR with a challenging task. Among previous work, Nguyen et al. [2] developed a superresolution technique for HRR-ATR using High Definition Vector Imaging (HDVI). Mitchell et al. [3] showed that the amplitude and location of HRR signature peaks could be used as features for target classification. Liao et al. [4] extracted features from each of the HRR waveforms via the RELAX algorithm before feeding those to Hidden Markov Model (HMM). Bhatnagar et al. [6] generated a hybrid system for HRR target classification.

Our previous work has demonstrated that by forming Eigen-templates via Singular Value Decomposition (SVD) and using normalized Matched Filtering (MF) for classification, excellent HRR-ATR performance in terms of Probability of Correct Classification (PCC) can be achieved [7]. It has been shown recently that appropriate hybridization of multiple optimization techniques can improve Speaker Recognition performance [5]. In this work, we propose a new Hybrid 1-D HRR-ATR technique where ETMF is combined with HMM to attain significant improvement in recognition performance. In this approach, the HRR test profiles are first scored by ETMF and then the *most likely* HMM models determined by ETMF are used for HMM scoring the at the second step. Final ATR decision is based on maximal ratio combining of the two individual scores. Performance comparison results are provided for Forced Decision as well as for Unknown Target scenarios. The unknown target scenario is simulated using the Leave One Out Method (LOOM) [9]. The performances of ATR algorithms are compared in terms of the Receiver Operating Characteristics (ROC) curves. The MSTAR data set is used for all simulations.

II. ETMF TECHNIQUE

SVD is a very effective and robust tool for decomposing any matrix into orthogonal basis spaces. As demonstrated in [8], the rank of a HRR-matrix formed using 1-3 degrees of detected HRR profiles is close to one, i.e., the largest singular value (λ_1) accounts for more than 80% of the total energy of the HRR range subspace of the underlying target.

Eigen based Feature Extraction: The SVD of a matrix of detected range profiles (Y) within a 1-degree sector of aspect angles produces three matrices: **U**, Λ and **V**:

$$\mathbf{Y} \xrightarrow{SVD} \mathbf{U}\Lambda\mathbf{V}^T = \sum_{i=1}^{M} \lambda_i \mathbf{u}_i \mathbf{v}_i^T \qquad (1)$$

where, λ_i denote the i-th eigenvalue, while $\mathbf{u}_i$ and $\mathbf{v}_i$ denote the corresponding left and right eigenvectors, respectively. The eigenvector corresponding to the largest eigenvalue λ_1 is used as the feature template for each 1-degree sector. However, before templates can be generated, the range profiles need to be aligned and properly normalized, as described next.

* This research was partly supported by AFRL, Wright Patterson AFB under contract: F33616-98-D1232/D00013

***Alignment of HRR profiles in Range**:* For template generation, adjacent range profiles in each 1-degree sector are aligned first with respect to their respective centroids (centroid-centroid matching). Then a profile is taken as a reference and the adjacent profile is shifted till maximum correlation is achieved. This procedure is repeated until all the profile centroids in a sector have been properly aligned.

*Classification***:** The recognition step is based on the Matched filter technique [9]. The decision determines the target type for which the correlation between its template (**m)** and the given observation (**a,** or test) profile is maximized among all template choices.

Normalization: Matched filter classifier (used in the recognition stage) assumes that both the observation ("Test") and template profiles are normalized. During correlation when the observation profile is shifted and correlated with the template profile, the region of overlap changes with each shift. Hence instead of normalizing the entire profiles, only the overlapping parts of the profiles are normalized before performing correlation [9].

III. HMM MODEL GENERATION

As the HRR profiles are not continuous stream of signals (each HRR profile is an independent return at a specific aspect angle), the discrete HMM model (DHMM) was used here. As HRR profiles are distributed between 0 and 360 degree, vector quantization (VQ) codebooks are created for each degree per target. Hence, there are a total of 360 codebooks per target at 1, 2, …, 360 degree. The cluster size in each Codebook (K) =128. As the number profiles per degree is limited, a total of 3-degrees of HRR profile information is used for each degree to make the codebooks more robust. In the discrete ergodic HMM approach, target dependent HMM model is made at each degree. The HMM parameters (**A**, **B** and π) are determined using Baum-Welch algorithm.

IV. Hybridization of ETMF and HMM

It has been demonstrated later that using a single range profile as observation ("test") the ETMF technique provides 81.5% forced target recognition, whereas the discrete HMM model recognizes only 66.67% target profiles correctly. Averaging of several profiles or multilook techniques can certainly improve the recognition rate further. However, for moving targets and tracking applications the position of target changes with time. Hence, it is advantageous to use a single profile at a time to obtain instantaneous track information.

Hence the primary motivation of hybridization of ETMF and DHMM is to achieve further improvement in recognition performance with a single range profile. Indeed, the results presented later show that the proposed ETMF-DHMM approach leads to significant increase in PCC with a single observation profile compared to either technique. It is assumed that MTI radar can provide correct aspect angle information within ± 1 degree. Hence, during testing each HRR profile is tested with 3-aspect angle templates per target producing 12 discriminant values. When the normalized ETMF technique selects the target having the highest discriminant value, sometimes it makes a wrong decision. The key idea behind the hybridization approach is that even if ETMF fails to score the correct target as highest, when combined with DHMM, better scoring can be achieved.

Some current hybrid techniques in literature [5], all the HMM models are used in scoring. However in case of HRR ATR, it was observed that even if not the highest, the correct target always remains in the top few discriminants, and hence we decided to use only a subset of the available discriminants. This approach reduces computation time and, more importantly, limits the number of confusers. As HMM has models for each target and aspect (same as ETMF), only those HMM models are used to score the HRR profile that gives high discriminant scores in ETMF testing. For each aspect angle, the exact number of HMM models to be used to score are to be determined from the training data. This technique of reduced HMM model scoring provides a 10-15% PCC improvement as compared to the case when all the HMM models are applied for scoring purposes.

For combining purpose, the ETMF scores are converted to probability before combining as shown in Fig. 1. If the correlation equals zero, the probability of that profile being the desired target also becomes zero, and as the correlation increases, the probability increases and approaches to one. Assuming ETMF and HMM techniques are statistically independent, the combined probability can be defined as:

$$P_{combined} = P_{ETMF} P_{HMM} \tag{2}$$

$$\log(P_{combined}) = \log(P_{ETMF}) + \log(P_{HMM}) \tag{3}$$

However since the performance of ETMF is much superior compared to that of HMM, log-likelihood score of ETMF is multiplied by a factor to provide ETMF more weightage compared to HMM.This weight is also predetermined from the training data and it is target and aspect independent. It only depends on the specific type of data used. For this data used here, the best choice for weight is to make ETMF contribution as 75% and HMM contribution as 25% on the combined score.

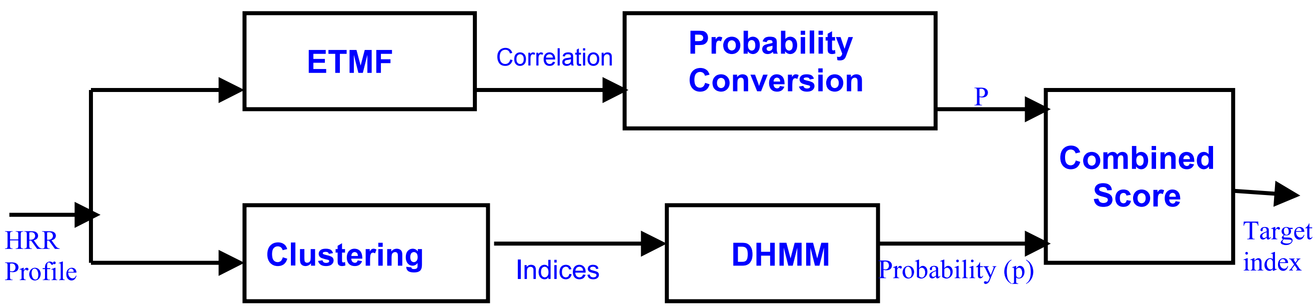

Fig1: Data flow in the proposed hybrid algorithm

$$\log(P_{combined}) = 3\log(P_{ETMF}) + \log(P_{HMM}) \quad (4)$$

The hybrid ATR algorithm selects the highest combined score and classifies it accordingly.

V. SIMULATION RESULTS

The proposed algorithms were tested using MSTAR data set containing HRR profile sets of 4 ground military vehicles (BMP2, T72, 2S1 and BRDM2) at 17 degree depression angle over 360 degree of aspect angles.

In this paper the result of the proposed ETMF–DHMM hybridization algorithm is compared with those of the individual techniques. Two types of classification tests are performed, namely Forced decision and unknown target scenario. The former assumes that all test targets belong to one of the known training target classes. The later makes no such assumption, so each test target needs to be compared with a threshold before making any decision whether it is known or unknown.

Forced Decision Result:

In case of Forced Decision the classification of the Target class with the largest likelihood determines decision for an observation profile.

The confusion matrices for individual ETMF, DHMM and the proposed hybrid technique for ATR with single profile are shown in Table 2, 3 and 4, respectively. It is found that PCC of the ETMF-DHMM hybrid technique is the highest. It can be seen that the performance of only HMM is relatively poor, but when it is combined with the ETMF technique, the overall PCC improves. This can be explained as follows: in case of MSTAR data, there are 59.76% of cases where both ETMF and HMM recognize correctly. Hence, for the (66.67-59.76)= 6.89% cases where DHMM method gave correct recognition but ETMF does not, the hybridization process has room for performance improvement.

The results of 3 and 5-profile sequence testing in all three cases are also shown in the Table 1. In all these cases the hybrid technique outperforms the stand-alone methods.

	1 profile	3 profile	5 profile
DHMM	66.67%	82.22%	89.34%
ETMF	81.5%	92.23%	94.12%
Hybrid	85.55%	93.82%	95.68%

Table 1: Summary of Forced Decision Results

Classification in Unknown Target Scenario:

In this case, the hybrid algorithm is applied to make classification decision in the unknown target scenario that is simulated by the rotating target class LOOM approach.

The results of this case are presented as three sets of curves. The first set is based on PCC vs. Probability of declaration (P_d). The second set deals with Probability of misidentifying an unknown target (false alarm) P_{fa} vs. P_d. The last one deals with PCC vs. P_{fa}. Results are shown for single and 3 profile sequence testing in Figs 3 and 4.

Target	**BMP2**	**T72**	**2S1**	**BRDM2**
BMP2	0.7727	0.0825	0.0682	0.0715
T72	0.0780	0.8330	0.0435	0.0455
2S1	0.0649	0.0334	0.8233	0.0784
BRDM2	0.0557	0.0475	0.0700	0.8269

Table 2: Confusion matrix for Eigen with single profile testing (PCC=81.5%)

Target	**BMP2**	**T72**	**2S1**	**BRDM2**
BMP2	0.6178	0.1302	0.1326	0.1194
T72	0.1315	0.7321	0.0830	0.0533
2S1	0.1207	0.0813	0.6725	0.1255
BRDM2	0.1214	0.0966	0.1404	0.6416

Table 3: Confusion matrix for DHMM with single profile testing (PCC=66.67%)

Target	**BMP2**	**T72**	**2S1**	**BRDM2**
BMP2	0.7731	0.0657	.0845	.0767
T72	0.0461	0.9233	0.0213	0.0094
2S1	0.0365	0.0134	0.8698	0.0603
BRDM2	0.0868	0.0378	0.0690	0.8364

Table 4: Confusion matrix for Hybrid algorithm with single profile testing (PCC=85.55%).

Fig 2: Performance comparison for sequence of 1, 3 and 5 profiles

In the unknown target scenario, the performance of the proposed hybrid ETMF-DHMM algorithm is compared with the ETMF alone. In Fig 4, we demonstrate that for same False Alarm probability, the PCC of the hybridized ETMF-HMM technique is significantly higher compared to that of the ETMF technique. It can also be seen that for same false alarm rate, the ETMF approach would need at least 3 observation profiles to attain the same level of PCC as achieved by the proposed hybridized ETMF-DHMM technique using only a single profile.

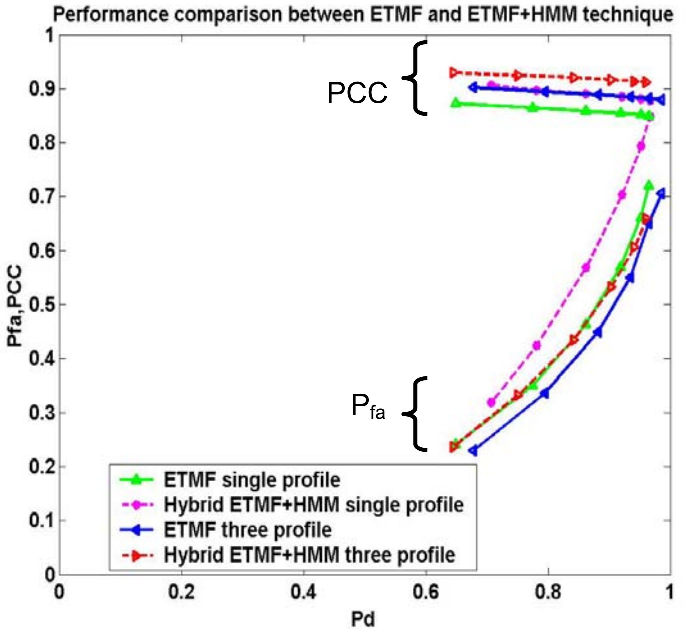

Fig 3: ROC curves for single and a sequence of 3 profiles for testing

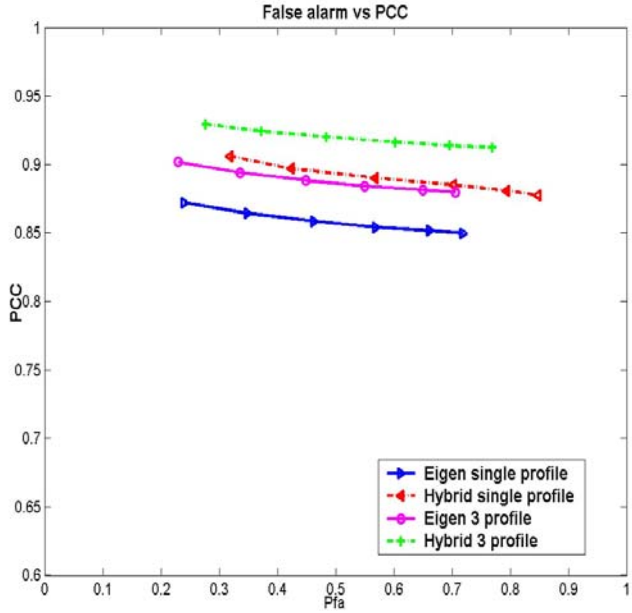

Fig 4: PCC comparison vs. various P_{fa}

Definition of P_d, P_{fa} and PCC:

P_d: Probability of target declaration assuming that the declared target is in the training database i.e. it is the probability that targets in the training set are not rejected as unknown.

PCC: Probability of correctly identifying a target provided that a target declaration is made.

P_{fa}: Probability of declaring an unknown target as a target in the training data set.

CONCLUSION

The main objective of this research was to demonstrate that improved classification of targets (PCC) could be achieved by hybridizing multiple HRR-ATR algorithms. We have demonstrated that the proposed hybrid ETMF-DHMM technique improves PCC significantly when compared to what is achievable by any one of the algorithms applied individually. For forced-decision case, our results show that the hybrid technique improves performance. For unknown target scenario, the hybrid technique with single profile achieves similar level of performance as that attained by the matched-filter based algorithm using at least three profiles.

ACKNOWLEDGEMENT

The authors would like to thank Bill Moore, Division Chief for the RF Sensor Technology Division, for his support of this research. The results of this research will be integrated into current simulation efforts for the research and development for advanced radar modes for future UAV platforms.

REFERENCES

[1] Novak, L.M., Owirka, G.J. and Weaver, A.L,"Automatic Target Recognition using enhanced resolution SAR data"*IEEE Transactions on Aerospace and Electronic systems*, 35(1), pp. 157-175, 1999.

[2] Nguyen, D., Benitz, G., Kay, J., Orchard, B. and Whiting R, "Superresolution HRR ATR with High definition Vector Imaging", *IEEE Transactions on Aerospace and Electronic Systems*, 37(4), 1267-1286, 2001.

[3] Mitchell, R.A. and Westerkamp, J.J., "A statistical Feature based Classifier For Robust High range Resolution Radar target Identification", *Automatic Target recognition Working Group*, Huntsville, AL, Oct 1997.

[4] Liao, X., Runkle, P., and Carin, L., "Identification of Ground targets From Sequential High Range Resolution Radar Signatures", *Technical report for AFRL and MRC.*

[5] Do M. and Wagner, M., "Speaker Recognition with Small Training Requirements Using A Combination of VQ and DHMM." *Proc. of Speaker Recognition and Its Commercial and Forensic Applications*, pp. 169-172, 1998.

[6] Bhatnagar, R., Horvitz, R. and Williams, R., " A hybrid system for Target Classification," *Pattern Recognition Letters*, pp: 1399-1403, 1997.

[7] Bhatnagar, V., Shaw, A. K. and Williams, R. "Improved Automatic Target Recognition using Singular Value Decomposition", *Proceedings of ICASSP 1998*, vol. 5, pp: 2717-2720, 1998.

[8] Shaw, A. K. and Bhatnagar, V., "Automatic Target Recognition using Eigen Templates." *Synthetic Aperture radar Imagery V: Proceedings of SPIE*, Orlando, FL, pp. 448-459, April 1998.

[9] Shaw, A K. and Vashist, R. "HRR-ATR using Eigen-Templates and Normalized Matched Filter as Classifier", *Synthetic Aperture radar Imagery V Proceedings of SPIE*, Orlando, FL, April, 2000.