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An Overview of Automatic Target Recognition Systems for Underwater Mine Classification

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Abstract— **The classification of real-world empirical targets using sensed imagery into different perceptual classes is one of the most challenging algorithmic components of radar systems. The contributions concentrate on feature selection and object classification. First, a sophisticated filter method is designed for the feature selection. This filter method utilizes a novel feature relevance measure, the composite relevance measure (CRM). The contributions concentrate on feature selection and object classification. The design of a single classification system, which was optimized in two fundamental aspects: the choice of the classification system and the selection of the optimal feature subset.**

***Keywords*— ATR,DST,SAS,CRM, Sonar Image,SAR**

I. INTRODUCTION

The classification of real-world empirical targets using sensed imagery into different perceptual classes is one of the most challenging algorithmic components of radar systems. This problem, popularly known as Automatic Target Recognition (ATR), exploits imagery from diverse sensing sources such as Synthetic Aperture Radar (SAR), Inverse SAR (ISAR), and Forward-Looking Infra-Red (FLIR) for automatic identification of targets. A review of ATR can be found in [1]. SAR image offers the advantages of day-night operation, reduced sensitivity to weather conditions, penetration capability through obstacles, etc. Some of the earlier approaches to SAR ATR can be found in [2]–[6]. A discussion of SAR ATR theory and algorithms is provided in [7]. The Moving and Stationary Target Acquisition and Recognition (MSTAR) data set [8] is widely used as a benchmark for SAR ATR experimental validation and comparison. Robustness to real world distortions is a highly desirable characteristic of ATR systems, since targets are often classified in the presence of clutter, occlusion and shadow effects, different capture orientations, confuse vehicles, and in some cases, different serial number variants of the same target vehicle. Typically the performance of ATR algorithms is tested under a variety of operating conditions as discussed in [7].

In ATR, like any other general image classification problem, representative features (i.e. target image representations) are acquired from sensed data and assigned to a pre-determined set of classes using a decision engine (or, in other words, a classifier). Although the eventual class decision is made by the decision engine, the discriminative capability of the features can significantly influence the success of classification. Further, different sensing mechanisms lend themselves to different types of useful features. Not surprisingly, initial research in ATR focused on the investigation of a variety of feature sets suitable for different domains of application [4], [9]–[11]. Equally important to classification accuracy is the choice of classifier. The application of different classifiers to ATR has mirrored advances in the field of machine learning. The success of margin maximization techniques like Support Vector Machines (SVM) [12] and boosting [13] as powerful classifiers has been demonstrated in the recent past [2], [14]. In spite of a proliferation of feature-classifier combinations, consensus has evolved that no single feature set or decision engine is optimal for target classification. This has spurred interest in combining the complementary benefits of multiple classifiers. Fusion techniques have been developed [14]–[18] that combine decisions from multiple classifiers into an ensemble classifier. These approaches reveal the presence of complementary yet correlated information present in distinct feature sets, which is exploited to a first order by fusing classifier outputs that use these features. In this paper, we develop a two-stage framework to directly

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model dependencies between different feature representations of a target image.

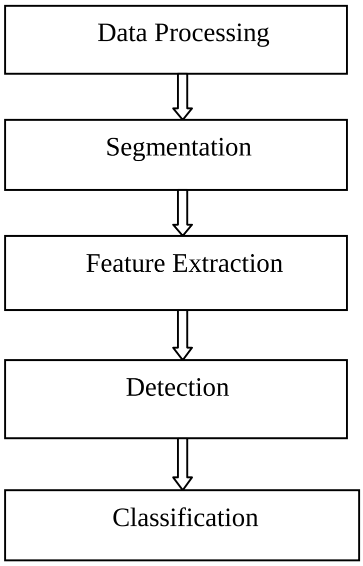

Fig1: Flow diagram of classification system

We argue that explicitly capturing statistical dependencies between distinct low-level image feature sets can improve classification performance compared to existing fusion techniques. The first stage involves the generation of multiple target image representations (or feature sets) that carry complementary benefits for target classification.

II. LITERATURE SURVEY

Tai Fei et. al. “Contributions to Automatic Target Recognition Systems for Underwater Mine Classification” in this paper deals with several original contributions to an Automatic Target Recognition (ATR) system, which is applied to underwater mine classification. The contributions concentrate on feature selection and object classification. First, a sophisticated filter method is designed for the feature selection. This filter method utilizes a novel feature relevance measure, the composite relevance measure (D-SFFS). Feature relevance measures in the literature (e.g., mutual information and relief weight) evaluate the features only with respect to certain aspects. The D-SFFS is a combination of several measures so that it is able to provide a more comprehensive assessment of the features. Both linear and nonlinear combinations of these measures are taken into account. A wide range of classifiers is able to provide satisfactory classification results by using the features selected according to the D-SFFS. Second, in the step of object classification, an ensemble learning scheme in the framework of the Dempster–Shafer theory is introduced to fuse the results obtained by different classifiers. This fusion can improve the classification performance.

Myers et. al. “Adaptive Multiview Target Classification in Synthetic Aperture Sonar Images Using a Partially Observable Markov Decision Process” in this author proposed the problem of classifying targets in sonar images from multiple views is modeled as a Partially Observable Markov Decision Process (POMDP). This model allows to adaptively determine which additional views of an object would be most beneficial in reducing the classification uncertainty. Acquiring these additional views is made possible by employing an Autonomous Underwater Vehicle (AUV) equipped with side-looking imaging sonar. The components of the multi view target classification POMDP are specified. The observation model for a target is specified by the degree of similarity between the image under consideration and a number of pre computed templates. The POMDP is validated using real Synthetic Aperture Sonar (SAS) data gathered during experiments at sea carried out by the NATO Undersea Research Centre, and results show that the accuracy of the proposed method outperforms an approach using a number of predetermined view aspects. The approach provides an elegant way to fully exploit multi view information and AUV maneuverability in a methodical manner.

R. Fandos et. al. “High Quality Segmentation Of Synthetic Aperture Sonar Images Using The Min-Cut/Max-Flow Algorithm” in this author proposed context of automatic detection and classification for mine hunting applications, a high quality segmentation of sonar images is mandatory. A Markov Random Fields representation of the images, propose a min-cut/max-flow segmentation algorithm. Introduce an original initialization of the graph cut algorithm based on the segmentation result of an Iterative Conditional Modes (ICM) segmentation approach. A large database of synthetic aperture sonar images containing 378 spherical and cylindrical man-made objects has been segmented using both the ICM algorithm and the graph cut approach. The sets of results automatically classified to a set of significant features. Results are compared.

III. METHOD

A. Feature extraction

Feature extraction has been always mutually studied for exploratory data projection and for Classification. Feature extraction for exploratory data projection aims for data visualization by a Projection of a high-dimensional space. Onto two or three-dimensional space, while feature extraction for classification generally requires more than two or three features. Therefore, feature Extraction paradigms for exploratory data projections are not commonly employed for classification and vice versa. For robust feature extraction, sonar images are symbolized by partitioning the data sets based on the information generated from the ground truth.

B. Classification

Title The challenging problem for the classifier is to identify features that will eliminate the false targets that have target strengths similar to the mine. The classifier provides excellent classification results based upon only the data of single aspect of the sonar. The threshold for the decision making is the one which makes the correct classification rate (Pcc) =1, false alarm rate (Pfα), i.e., the point where misclassification rate is equal to the false-alarm rate. A classification procedure is required to determine whether the detected object is a false alarm or not. While many systems define classification as simply determining whether an object is mine or not-mine, geometric analysis can be used in the classification stage to determine the shape of the object. Mines can often be described by simple objects such as cylinders, spheres, and truncated cones, therefore ensuring that, if the MLO can be classified as one of these objects, it can be identified as a mine with a high degree of confidence. Bryan Thompson, Jered Cartmill, Mahmood R. Azimi-Sadjadi, and Steven G. Schock (2006) examined CCA-based decision-level fusion classifiers. The classification results will indicate the robustness of the extracted CCA/MCCA features as well as the generalization ability of the classifiers. Next, classification systems able to classify objects based on individual feature vectors produced via both the CCA and MCCA feature extraction methods are developed. Two classifiers are created, one is trained using individual CCA feature vectors, and the other using feature vectors produced via the MCCA method W. Kenneth Stewart, Min Jiang, and Martin Marra (1994) proposed a Back propagation neural network Classification. During classification, information passes through the network in one direction from input layer, through hidden layer(s), to output layer. Each node actually performs two functions, collecting the activation from nodes of the previous layer and setting output activation.

Jin-wei Li et. Al. “Noise Filtering of High-Resolution Interferograms Over Vegetation and Urban Areas With a Refined Nonlocal Filter” The high-resolution interferogram over vegetation area is heterogeneous due to open canopy gaps, visible ground, and different plant structure, whereas the interlaced different scattering media are responsible for the heterogeneity of urban areas. The heterogeneity will break the local stationarity as sumption and degrade the performance of traditional filters. The refined nonlocal filter proposed in this letter can identify the outliers and remove them from the filtering process. The experimental results show that the proposed method could reduce the interferometric noise effectively and make the edges between different scattering media well preserved. In addition, the reason for the better performance of the pseudo coherence defined as maybe that it can mitigate the effects of the amplitude heterogeneity in the window, and the reason will be investigated further in the future.

Gaohuan Lv et. Al. “Synthetic Aperture Radar Based Ground Moving Target Indicator Using Symmetrical Doppler Rate Matched Filter Pairs” In this paper presented an SDRM filters based GMTI scheme to detect the presence of moving targets and estimate their azimuth velocities in a single complex SAR image. The scheme works fast and effectively during our experiment. A feature criterion to determine the presence of the moving target is defined by the sharpness ratio in a patch in the two derivative SAR images. An SDRM filter pair processes a given SAR imagery and achieves two defocused SAR images that have the same defocused background but different defocused moving targets, and then by comparing the sharpness of the two images, the moving targets are determined adaptively and automatically. The azimuth velocity estimator utilizes an SDRM filter pair bank to get azimuth velocity of detected targets.

IV. CONCLUSIONS

The design of a single classification system, which was optimized in two fundamental aspects: the choice of the classification system and the selection of the optimal feature subset. We propose a reasonable construction of the Basic Belief Assignment (BBA). The BBA considers both the reliability of the classifiers and the support of individual classifiers provided to the hypotheses about the types of test objects. Finally, this ATR system is applied to real synthetic aperture sonar imagery to evaluate its performance..

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