A NEW METHOD OF SAR IMAGE TARGET RECOGNITION BASED ON ADABOOST ALGORITHM

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We propose a novel SAR (Synthetic Aperture Radar) automatic target recognition framework that is capable of processing images extremely rapidly while achieving high recognition rates. This SAR ATR system is used for classification of three types of ground vehicles in the moving and stationary target acquisition and recognition (MSTAR) public release database.

The MSTAR data is a standard dataset in the SAR ATR community, allowing researchers to fairly test and compare their ATR algorithms. Among these systems, some commonly used approaches are proposed, such as principle components analysis (PCA), template-based method, neural network, and so on. Recently developed large-margin-based algorithms have been reported to alleviate the overfitting problem, while at the same time maintaining the classification efficiency. Two typical examples of the margin-based classifiers, the support vector machine (SVM) and AdaBoost, are successfully used in pattern recognition fields. Concerning AdaBoost, the literature reports success of many AdaBoost-based systems for pattern classification. Nevertheless, it has not yet gained appropriate attention in the SAR ATR community.

We introduce a novel classification scheme for the MSTAR data using the AdaBoost algorithm. And we also describe how AdaBoost algorithm can be used as a multiclass classification method as well as a feature fusion method. The features selected by AdaBoost are meaningful and have high discriminative power. We have gotten some fine results after large-scale experiments. When all the available training data (seven serial numbers of the three vehicle classes) is used, our system achieves 97.12% correct classification rate. To our knowledge, this is an excellent result ever reported in the literature. When only a subset of the training data (only three serial numbers, one per vehicle class) is used, our system achieves 95.84% correct classification rate. This means that our system has a very good generalization capacity.

The most important property of AdaBoost is its ability to find a highly accurate ensemble classifier by combining a set of moderately accurate member classifiers, called hypotheses or base learners. AdaBoost guarantees an exponential decrease of an upper bound of the training error with the increase in the number of hypotheses, subject to a mild constraint that each base hypothesis achieves an error rate less than 0.5. Moreover, both theoretical and empirical results demonstrate that AdaBoost has an excellent generalization performance.

There are three key contributions. The first is the introduction of a new pose estimation algorithm, whereby all targets are rotated to the same aspect angle. We represent MSTAR images by two sets of image features. The first set, called raw features, represent pixel values of the original image chips that are not preprocessed. The second set of features, called fine features, comprises magnitudes of two-dimensional
discrete Fourier transform (DFT) coefficients computed on the aligned image chips, which are rotated to the same aspect angle by the pose estimator. Here, it is necessary to design an efficient data fusion method for combining the two highly correlated feature sets.

The second contribution of this paper is the scheme for preprocessing the MSTAR data. Unlike in optical images, targets in SAR images do not have clear edges. To detect edges, it is first necessary to segment targets from noisy background, and then detect edges of the segmented targets. The procedure of preprocessing includes histogram equalization, smoothing, rough target segmentation, fine target segmentation, edge detection, dilation, etc. The experimental results, reported herein, show that the outlined classification system, with the preprocessing of the MSTAR data, achieves comparable performance to that of systems utilizing sophisticated pose estimators. This means that our SAR ATR system can be implemented for the applications with stringent real-time constraints.

The third major contribution of this paper is a simple and efficient classifier that is built by selecting a small number of important features from a huge library of potential features using AdaBoost learning algorithm. Within any image sub-window the total number of Haar-like features is very large, far larger than the number of pixels. In order to ensure fast classification, the learning process must exclude a large majority of the available features, and focus on a small set of critical features. Motivated by the work of Tieu and Viola feature selection is achieved using the AdaBoost learning algorithm by constraining each weak classifier to depend on only a single feature. As a result each stage of the boosting process, which selects a new weak classifier, can be viewed as a feature selection process. Then, the chips are classified by using the AdaBoost algorithm with the radial basis function (RBF) network as the base learner. Since the RBF network is a binary classifier, we decompose our multiclass problem into a set of binary ones through the error-correcting output codes (ECOC) method, specifying a dictionary of code words for the set of three possible classes. Along with classification, within the AdaBoost framework, we also conduct efficient fusion of the fine and raw image-feature vectors.

The rest of the paper is organized as follows: Section 2 gives the introduction of our data preprocessing, including the pose estimation and image-feature representation. Section 3 gives a brief review of AdaBoost and the RBF network, as well as discuss how to use AdaBoost for feature selection and fusion and ultimate multiclass target recognition. Experimental results on the MSTAR data are presented and discussed in Section 4. Finally, discussion and conclusions will be given in section 5.

REFERENCES