Automatic Image Based Classification Capabilities of Targets for Passive ISAR

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ABSTRACT

We present research results in range/cross-range image feature based automatic target extraction and classification for multistatic passive Inverse Synthetic Aperture Radar (ISAR). The method performs automatic analysis of passive 2D ISAR images to evaluate the possibilities and capabilities of image feature based target extraction and classification. The goal is to extend signal processing based detection and recognition methods with image information. The presented method is fast, easily embeddable and extendable, works near real-time, and we show its viability for classification using real passive 2D ISAR images.

1.0 INTRODUCTION

Passive radar systems use one or more non-cooperative illuminators of opportunity (e.g., digital video broadcasts [1], mobile communications [2], digital or FM radio [3], etc.) as signal sources and one or more controlled receivers. Passive radars have recently received a renewed interest from the scientific community since the recent technological advances have made the realization of low cost passive radars [4] and real time processing possible. Following the recent technological advances on this field, additional radar techniques are added to passive radars to make them able to handle several tasks. One of such task is the radar imaging [5] of non-cooperative targets with the use of Inverse Synthetic Aperture Radar (ISAR) methods [6], [7], [8], which in turn may open the door to Automatic Target Classification (ATC). Although recent researches have demonstrated the feasibility of passive radar imaging, the ability to use these ISAR images for target recognition was formulated but not demonstrated. This paper is an attempt to prove whether 2D ISAR passive radar images can be used for such a purpose.

This paper focuses on target segmentation and classification using 2D ISAR range-crossrange images of passive radar systems [9]. The goal of the proposed method is to have a generic, model-free approach for image-based target recognition that can be used for various target classes and image resolutions with a low number of target samples, but can be easily extended to support larger target classes. The most important application area is silent, passive defense observation for force and area protection (e.g., [4]). Passive radar technology has been applied to target detection and imaging [2], [7] and for target classification [10], [11], [12] using signal or image processing approaches. Our goal is to extract targets and features from 2D passive ISAR images originating from a multistatic passive radar measurement system that can be used for image-based classification. When we know possible target structures, works like [12], [13] provide detection methods using a Markovian approach. However, our goal is to detect targets without target model constraints.

The contribution of the current work is that it proposes a lightweight solution, without the need of periodic retraining, that can also work with a low number of examples. The proposed method produces a segmentation of the target from 2D passive ISAR images, based on previous results in saliency based feature map generation [14], [15]. First, we produce a fused feature map of directional and textural salient information, then we extract target regions and their contours as a basis for classification using shape based recognition and retrieval [16].

The proposed approach has been tested on data acquired with the SMARP (Software-defined Multiband Array Passive Radar) passive radar demonstrator, developed by the Radar and Surveillance Systems Laboratory (RaSS Lab.) of the Italian National Inter-University Consortium for Telecommunications (CNIT). SMARP is a dual band and dual polarization passive radar operating at UHF (470−790 MHz) and S-band (2100−2200 MHz). In its current version SMARP is able to acquire up to 25 MHz bandwidth signal at UHF [4].

This paper reports recent findings achieved in and after the EDA project MAPIS [17] (Multichannel Passive ISAR imaging for military applications), a consortium composed by 9 entities from 5 countries; National Interuniversity Consortium for the Telecommunications (CNIT) (IT) acting as Project Leader, LEONARDO (IT), MBDA (IT) University of Alcalà (UAH) (ES), Fraunhofer Institute for High Frequency Physics and Radar Techniques (FHR) (DEU), Warsaw University of Technology (WUT) (POL), PIT-RADWAR (PR) (POL), Institute for Computer Science and Control, Hungarian Academy of Sciences (SZTAKI) (HUN), Budapest University of Technology and Economics (BME) (HUN).

2.0 THE PROPOSED APPROACH

The main goal of the approach proposed in this paper is to provide a method that can work with a limited dataset, but can scale to a larger number of samples as well. The method has two steps: i). detection and extraction of targets from range-crossrange images, along with target features, and ii). classification of the extracted target based on previously seen samples.

The dataset that we used for processing and testing contains real range-crossrange images produced by passive ISAR measurements and contains images of targets from 8 classes, 128 images in total. Figs. 1 and 2 show examples of input images that we process for detection and classification.

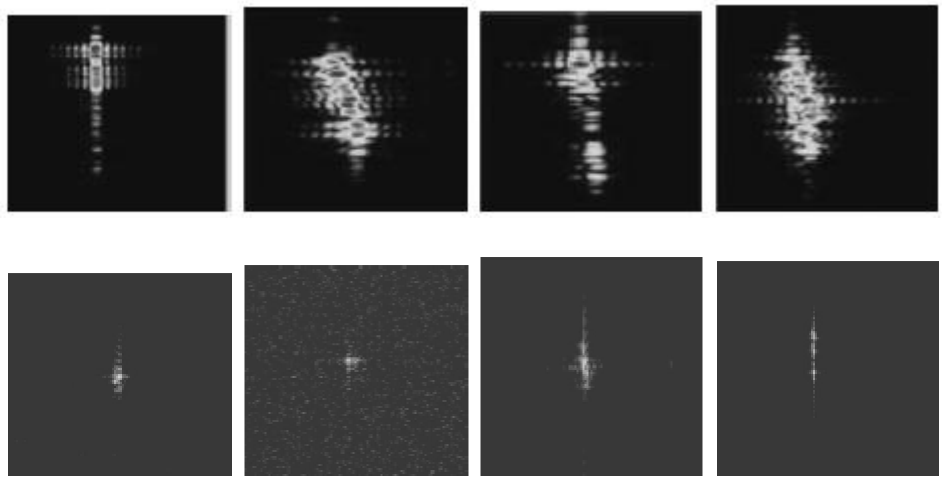

Figure 1: Example raw input range-crossrange images.

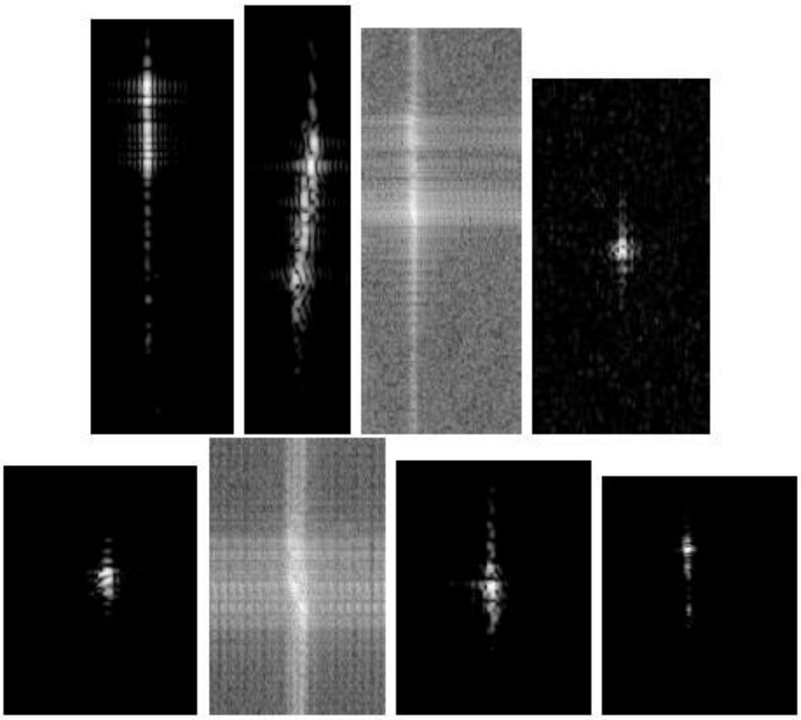

Figure 2: Example input range-crossrange images resized according to real size ratios.

2.1 Target Extraction

The proposed method is generic, in the sense that does not use any a priori target information (shape, model, etc.), but relies only on discriminative image features. A benefit of such an approach is flexibility and independence from possible target model constraints. The goal is the detection of the target candidates, and the extraction of features that can later be used for classification and recognition. The method that we propose is based on the extraction of fused morphological, textural and edge feature maps. The final features that we aim to extract and retain are the shape/contour of the target and its length.

Input images can be of various size and resolution, and they can contain targets with different meters/pixel resolution. As a first step, we resize the raw inputs to have a ratio consistent with their resolution (e.g., Fig. 2).

The main concept of the proposed detection and extraction is to first extract the salient object - target candidate - in the image, then use the features of this object in the classification step. As a first step of the object extraction, a texture map is calculated by using the sparse texture model of [18] and measuring the statistical textural distinctiveness of the occurring texture atoms. The number of these atoms can be set beforehand, and is usually chosen quite low, resulting in a sparse texture model of the image (the original method used 20 texture atoms, and we also use the same throughout the experiments), using the atoms to classify image regions.

Among the atoms, the salient atoms are searched as those areas of the image that draw visual attention by defining a statistical texture distinctiveness value for each atom. Passive ISAR images are different from general imagery, however the main rules still hold: more distinct regions have higher statistical texture distinctiveness. Also, in such images the target is usually close to image center, which also attracts higher visual attention, therefore these image areas require higher distinctiveness. The calculated T texture map is shown in Fig. 3(b), where higher distinctiveness is represented by lighter color. The texture map is binarized with adaptive Otsu thresholding [19] to define the initial salient blob (Fig. 3(c)).

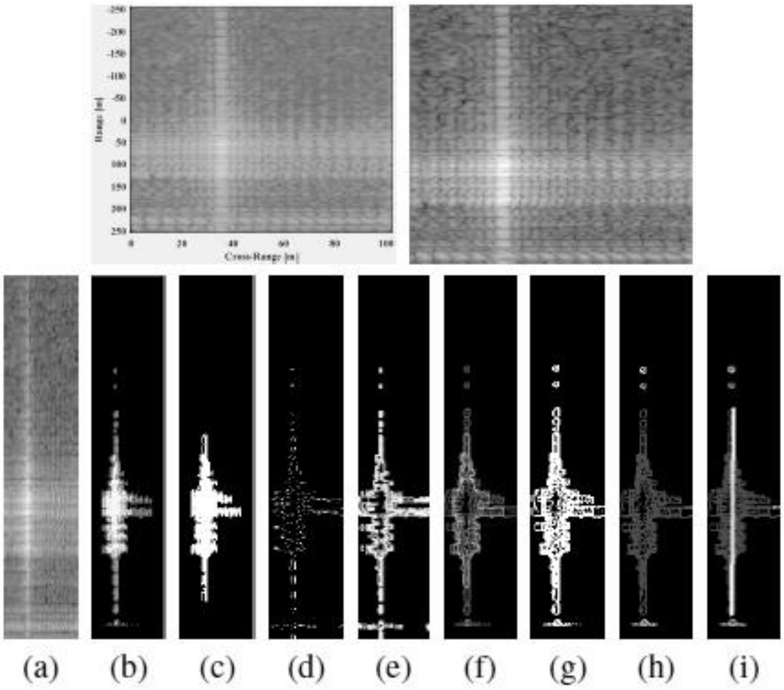

Figure 3: The process of the segmentation and extraction.

For salient object extraction, the first step is a robust object outline detection, which is a great challenge in case of passive ISAR images, as edges can be quite blurry. To compensate for this challenge, the keypoints of the detected salient area are extracted and salient directions are calculated based on the main orientations of the gradient in the small surroundings around the keypoints. This orientation feature is then used for an improved edge enhancement by building a structural feature map.

A modification of the Harris characteristic function [21] was introduced for noisy and high curvature boundaries [20] for keypoint extraction. Keypoints are calculated as the local maxima of the Modified Harris for Edges and Corners (MHEC) function, which is based on the eigenvalues (λ_1 and λ_2) of the Harris matrix:

$$R_{\text{mod}} = \max(\lambda_1, \lambda_2)$$

The calculated MHEC keypoint set is shown in white in Fig. 3(d), the points are selected in the *P* keypoint set if they have R_{mod} value over an adaptive Otsu threshold. Based on the P point set, features are searched for object contour enhancement. Local direction as a feature [22], [23] may facilitate contour detection by defining the main orientations where relevant edges should be searched for. To handle multiple orientation cases (such as corners) and to calculate proper direction information (not only histogram binning) on a contour level (not only pixel level), the direction feature extraction algorithm introduced in [24] was applied and then the Morphological Feature Contrast (MFC) operator [25] was used for edge detection.

The MFC operator first distinguishes background texture and isolated salient features, and it has an extension to extract linear features in defined directions. By applying this extension in the previously extracted main orientations, the relevant features can be emphasized. By fusing this Salient Direction feature map (M_{SD}) with the MHEC function (R_{mod}), the structural information of the salient area is enhanced in an *S* structural feature map, which is shown in Fig. 3(e) and is calculated as follows:

$$S = \max(\max(0, \log(M_{SD})), \max(0, \log(R_{\text{mod}})))$$

To also incorporate textural information, the T texture map (Fig. 3(b)) is fused with the S structural feature map (with γ=0.3) resulting in an improved object contour representation (Fig. 3(f)):

$$C = \gamma \left|\nabla(S(x,y))\right| + (1-\gamma)\left|\nabla(T(x,y))\right|$$

By applying adaptive Otsu thresholding on the C object feature map, the binary contours are defined (Fig. 3(g)) for further processing steps. The 5 biggest blobs are selected, followed by the extraction of contiguous blobs and extracting their contours (Fig. 3(h)). After ordering the blobs by size, the largest one is selected as the target candidate and its main length is measured (Fig. 3(i)). Fig. 4 shows some examples for input images and the final results of the above described target detection and extraction steps.

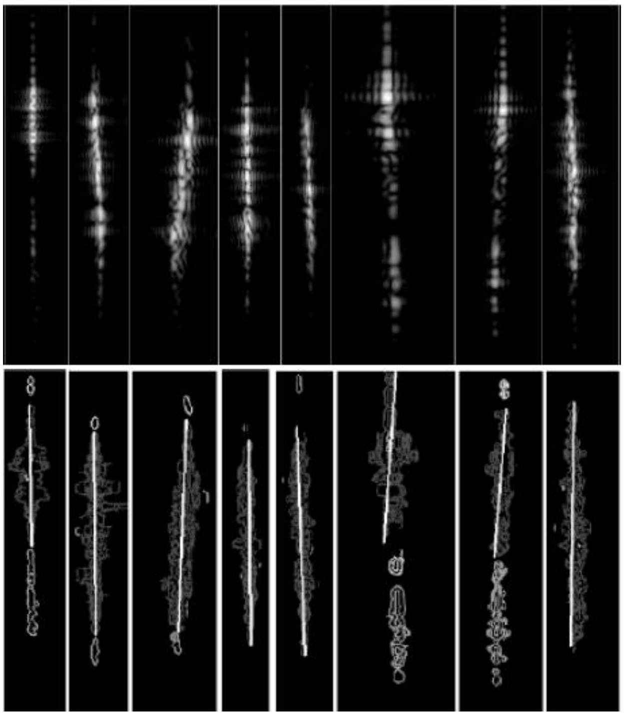

Figure 4: Examples of input images (top) and final extracted regions and main lengths (bottom).

2.2 Classification

The proposed classification solution does not need periodic re-training, is easy to extend with new target classes, and is part of a classification process that is invariant to target rotation.

First, we take the targets extracted from the previous step, and extract their contours. For classification, the contour of the candidate is transformed into a rotation invariant tangent function representation [26]. To obtain a target class estimate, we propose a method based on [16], with a point of view of content based retrieval. Using the available labeled dataset, we construct an index structure [27] which indexes the dataset based on the comparison of the extracted shape descriptors

In this solution, the classification of a target becomes a content based retrieval step: an input target is a query, and we find the most similar nodes in the index structure, assigning the class of the most similar results as the class of the queried target. Using the shape representation of an extracted target, we classify the target by performing a retrieval step on the available index and taking the best results as an indicator of the class.

3.0 EVALUATION

We used a dataset of 128 real passive ISAR range-crossrange images of 8 targets, 2 aerial (planes), 6 nautical (ships). We label these classes with letters A to H.

Using the above described index structure, we performed retrievals on the indexed dataset to find target classes. For evaluation, we indexed the dataset and performed retrievals for each dataset element, discarding the first result (which was always the input/query image).

For our evaluations, for each queried target image, we retrieve the 10 closest matches and take the majority of the results as the class estimate. Fig. 5 shows the normalized confusion values of the classification using the full dataset, and Fig. 6 shows the average recognition rates for the used classes. From these results we can see that some classes were well recognized (94%), others had a lower recognition rate (28%), the average recognition rate being 61%.

	A	B	C	D	E	F	G	H
A	0.64	0.14	0.21	0.00	0.00	0.00	0.00	0.00
B	0.00	0.38	0.06	0.13	0.00	0.19	0.00	0.25
C	0.13	0.00	0.67	0.07	0.07	0.00	0.00	0.07
D	0.00	0.27	0.18	0.55	0.00	0.00	0.00	0.00
E	0.00	0.00	0.00	0.00	0.56	0.00	0.33	0.11
F	0.00	0.17	0.06	0.06	0.06	0.28	0.33	0.06
G	0.00	0.00	0.00	0.00	0.07	0.00	0.93	0.00
H	0.00	0.06	0.00	0.00	0.00	0.06	0.06	0.83

Figure 5: Normalized confusion matrix.

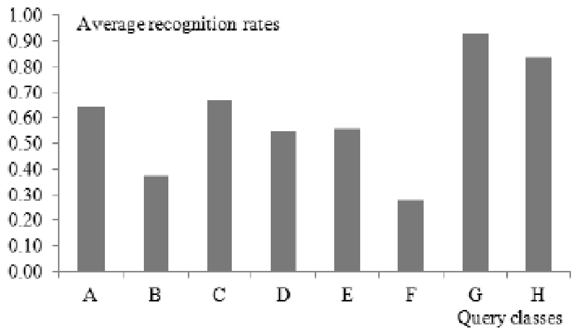

Figure 6: Average recognition rates for the proposed method.

To put these results into perspective, we also evaluated other classification methods on the same dataset. First, we ran SVM (support vector machine) classifications, using histogram of oriented gradients and local binary pattern features, and we show the classification results in Fig. 7. We used the Matlab SVM implementation and tried linear (SVML), Gaussian (SVMG), RBF (SVMR) and polynomial (SVMP) kernels. We also tried decision tree (Dec.tree) and k nearest neighbor (kNN) learner templates. All versions were run 10 times, with random 75% of the dataset used for training and 25% for testing, and averaging the results. The results show that the best SVM average (SVML+HOG: 70%) is similar to our proposed results.

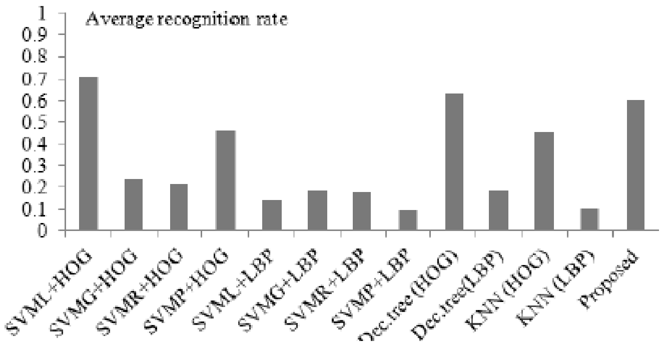

Figure 7: Average recognition rates for the SVM approaches, the decision tree and kNN methods and the proposed method.

To showcase another benefit and strength of the proposed approach, we performed another evaluation step. We created 2 rotated (with 45 and 135 degrees) versions of 1 raw input image from each class (16 images in total), and tried to classify these rotated versions using the proposed approach and the closest methods from Fig. 7. The rotated images were not included in the indexing and in the model training steps, only used as unknown input targets. Fig. 8 shows some examples of such rotated images. The goal of this evaluation step is to show that the proposed method is strong in recognizing the class of targets which are rotated versions of targets seen before (i.e., have samples of the target in the index, but from different angles).

Fig. 9 shows average recognition rates for the rotated inputs (2 images for each class, averaged). The results show that the proposed method could correctly classify the rotated targets, while the other approaches mostly failed.

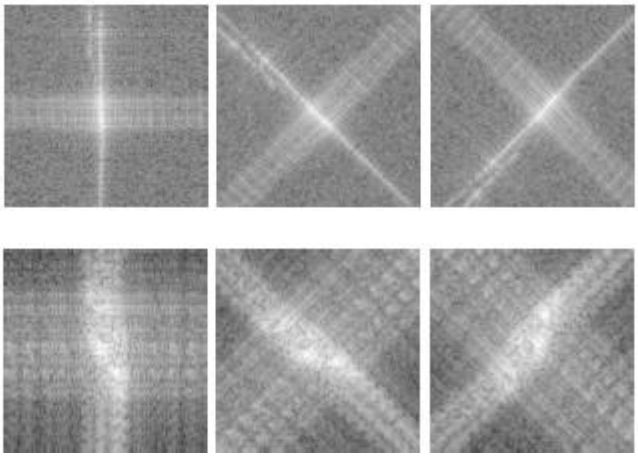

Figure 8: Samples of artificially rotated raw inputs.

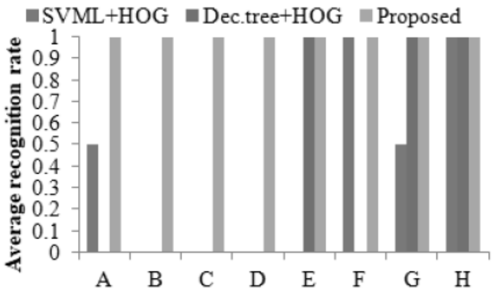

Figure 9: Average recognition rates for the rotated inputs for the 8 classes (A-H).

4.0 CONCLUSIONS

We presented an automatic target extraction and classification method for passive multistatic ISAR rangecrossrange images, to showcase the possibility of image feature based approaches for such tasks. The presented method treats classification from a content based retrieval point of view, with several benefits:

- It can work with a small number of samples but it is easy to extend with more data.
- It is lightweight and can handle multi-target classification.
- It is rotation independent, and it does not need different rotations to be included in the training dataset. Other approaches would need all possible (or preferred) rotated versions to be included in training.
- It can robustly extract the contours of the target and use it as a basis for classification, thus it is more robust than other approaches that classify based on overall image statistics, and it can better handle the classification of unknown variations.
- Adding a new element to the dataset means one addition to the index, while the other methods would need to be retrained (including all preferred distortions) when extending the dataset.
- Its robustness can be increased by incorporating more variations of class samples.

The proposed approach is lightweight enough to be embeddable to existing ATR systems that incorporate passive multistatic ISAR imaging.

5.0 ACKNOWLEDGMENTS

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