AUTOMATIC TARGET RECOGNITION IN SAR SCENARIOS BASED ON A NOVEL CLASSIFICATION SCHEME

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1 INTRODUCTION

Target classification in SAR scenarios is one of the main ATR (Automatic Target Recognition) tasks. In extended scenarios ROIs (Regions Of Interest) containing target hypotheses are detected. This can be done by MTI (Moving Target Indication) or in the case of stationary targets by other screening algorithms, e.g. hot spot detection. Hence, the proposed processing chain consists of a screening process identifying ROIs with target cues, a data pre-processing, and a high-performance classifier, see Figure 1. The screening method should provide all specified targets whereas the number of false object hints is of lower interest. Concerning the high FAR (False Alarm Rate) it follows that the quality of the classification step depends significantly on the classifier's capability to reject non-trained and clutter objects.
Due to their high robustness and good generalization properties kernel machines like the Support Vector Machine (SVM), see [2, 7], are chosen as classifier. In general, kernel-machines are two-class classifiers. This implies the need for a decision method to handle multi-class problems.

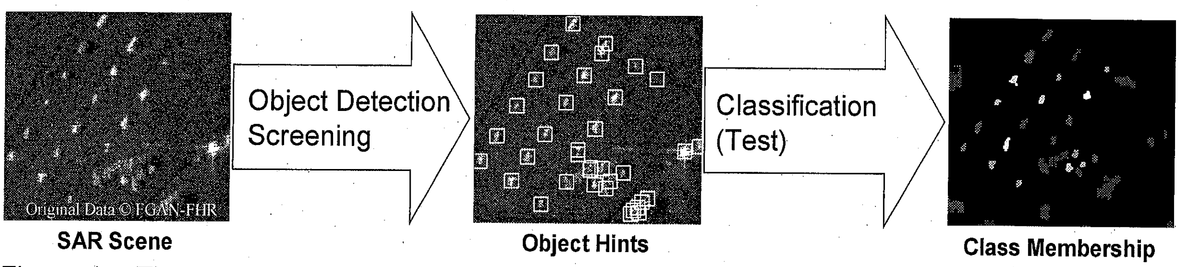

Figure 1. The target recognition processing chain consists of a screening and a classification module with integrated pre-processing.

In previous investigations [3, 4] using a kernel-based classification the reject of false alarms has been achieved by means of a heuristic, taking into account the classes differences. It does not employ the complete available information about class membership. In general, membership assessment and class discrimination are the main concepts in classification. The kernel machines used are two-class classifiers with good discrimination properties. However, a function for class membership assessment is necessary rejecting objects that not belong to the trained classes. Both aspects the membership assessment as well as the class discrimination are incorporated by the novel SVM21. This scheme uses class discriminating information computed in a pre-classification step to boost the succeeding main classifier that is responsible for membership assessment.

In Section two the target screening of SAR scenes and the pre-processing of SAR image chips are discussed. It follows the review of our previous investigations concerning the heuristic method in section three. The novel SVM21 classification scheme is presented in section four. Section five comprises the results of experiments with a SAR dataset provided by QinetiQ and the public MSTAR dataset. A conclusion is given afterwards.

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2 SCREENING AND PRE-PROCESSING

Before the target classification takes place the scenes have to be screened for object hints. A screening method has to fulfill the following demands:

- The generated hypotheses have to contain all specified targets
- Low computational effort
- Easy to use, i.e. it depends only on a few parameters
- Ability of processing huge amounts of data
- A good data reduction

Here, these demands are tailored with respect to the vehicle classifcation in SAR scenarios. Our investigations are focused on SAR sensors with a resolution between 30cm and 40cm. Therefore, the considered vehicles are represented by not less than 200 pixels and can be placed in a bounding box of 64x64 pixels. Moreover, for vehicles most of the significant pixels are brighter than the target's surrounding.

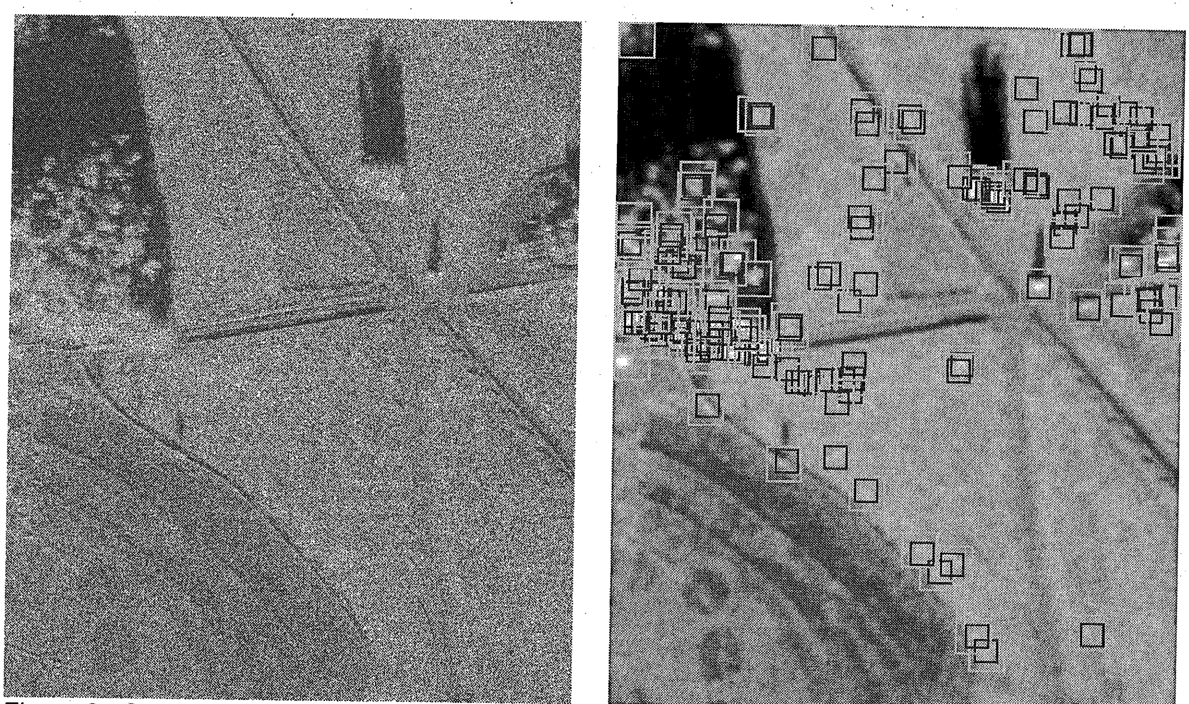

Figure 2. Screening a SAR scene. Left: original SAR magnitude image, Right: Gaussian smoothed, screening hints (outer green boxes), cropped centered targets (inner red boxes)

Possible detection methods are e.g. hot spot detectors and segmentation based pre-selection. We have used a simple hot spot detector. In the first step the scene is smoothed by a Gaussian filter with standard deviation of 5.0. By this, the speckle is reduced. In the second step the local maxima are determined. Usually each target is represented by one local maximum. The most significant hints are chosen with respect to a user defined threshold. In Figure 2 (right) the accepted screening hints are given as green boxes in the smoothed SAR image.

The classification module demands targets with well defined positions. Taking this into account, the objects detected by the screening task have to be adjusted accordingly. In the proposed processing chain this requirement is satisfied by a target centering. Based on the 100 brightest pixels the center of gravity is calculated as the desired unique target position. The target chip is cropped as 64x64 window around this position. In Figure 2 (right) the centered targets are marked with red boxes in the smoothed SAR image.

Data consistency is a prerequisite for achieving good classification results. Therefore a correct calibration of the SAR data is necessary. Additionally we apply a normalization to the data.

3 PREVIOUS INVESTIGATIONS

The classification module is applied to the cropped image chips selected by the screening process. Its main features should be robust classification, improved multi-class capabilities and adaptability to the users' requirements concerning classification quality versus FAR. In our proposal a family of basic kernel-classifiers automatically performs the feature extraction. According Byun and Lee [1], we utilize RBF (Radial Basis Function) kernels in our investigations as there is no knowledge about the classes' structure.

Typically, the SVM only solves 2-class problems. An adaptation to multi-class problems is achieved by means of a decision heuristic. This procedure applies one classifier for each pair of classes followed by a two-stage heuristic based on the accumulated class voting. In this context, the three most favorable classes are determined and directly compared with each other. Additionally, a user-controllable reject criterion is given in the high dimensional feature space implicitly defined by the classifiers' kernel. In this space the classification is accomplished by linear discrimination. Thus, hyperplanes c_{ij} define the boundaries between all pair *(i,j)* of classes. An acceptance region is specified by the minimal distance d_{min} to all related hyperplanes. Thus, samples may be rejected by means of two reasons. First, a reject occurs if the decision heuristic does not achieve an unambiguous class voting. Second, a sample is rejected by the parameterized reject criterion. Hence ROC (Receiver Operator Characteristics) curves can be computed, presenting the interrelationship of the FAR and the classification quality. In previous investigations [3, 4], this approach was confirmed to be powerful and robust for several data sets. Nevertheless, the classifier accepts clutter objects not belonging to the trained classes. Hence, the discriminatory power of the reject criterion should be further increased. Moreover, from a methodological point of view, a voting strategy is often less desirable than a pure functional concept.

4 CLASSIFIER DESIGN

In general, membership assessment or class discrimination is applied for solving the classification problem. To be able to reject objects not belonging to the trained classes, the evaluation of membership assessments is necessary. A kernel method suitable for solving this task is the so-called 1-class SVM, see [5, 6]. When using the RBF kernel machines, a single kernel parameter defines the input classes clustering fineness and gives different generalizations with respect to class-clutter-distinction. Additionally, the reject is controlled by a single user-defined threshold adjusting the system's selectivity.

4.1 The One-SVM for Multi-Class Problems

The 1-class SVM [5, 6] was tested using the original data *o* without any feature extraction or pre-classification. At first, the membership assessments $c_k(o)$ for the n different classes are computed. Then, the class with the highest membership assessment $c_k(o)$ is accepted as final classification result. A reject occurs if the membership assessment is lower than the user-defined reject threshold *TOL*.

This classification scheme depends on the kernel parameter as well as the reject threshold. It is easily upgraded with respect to new classes as the informational linking of the classes' evaluations takes place at the end of the process. Furthermore, the computational effort is rather low. But, unfortunately, this classifier is not supported by information from class discrimination. Additionally, this method requires a balanced scale of all membership assessments. Unluckily, there is no guarantee that 1-class SVMs are fulfilling this basic requirement. If this is not the case, objects positioned near the class borders may be classified wrongly.

4.2 The SVM21 Approach for Multi-Class Problems

Taking the mentioned demands into account, our proposed SVM21 method is operating on the results obtained by applying 2-class SVMs as pre-classifier supporting the class discrimination and the necessary normalization. Hence, the original data o is pre-classified using a scheme of 2-class SVM test functions for discriminating between all pairs of the n classes. By this, a new feature vector is generated with $N = n(n-1)/2$ elements. However, the separation of one class from all other classes is achievable using only the results of $(n-1)$ classifiers. Especially, the outcomes of all other ones corrupts oftenly the final decision. Therefore, class-dependant feature vectors $c_k(o)$ are deduced from the full-size feature vectors $c(o)$ consisting only of the results of the classifiers separating class k from all other classes. Afterwards, the 1-class SVMs determine membership assessments $v_k(c_k(o))$ for each of the n classes operating on these new feature vectors $c_k(o)$. Then the best evaluated class is accepted as final classification result. Again, a reject will occur, if the related membership assessment is lower than the user-defined reject threshold TOL.

An advantage of our approach is the usage of class discriminating features. The dimension of the deduced feature vectors is low, the computational effort is slightly higher than the one our previous method with decision heuristic. Finally, the novel SVM21 method depends on the kernel parameters of the 2-class SVMs and the 1-class SVMs, and the reject threshold TOL of the 1-class SVMs.

5 EXPERIMENTS

As mentioned before a good classification rate and the capability to reject objects not belonging to one of the trained classes are the main demands of a successful classifier. In order to test whether the integrated reject criterion fulfills this demand, the following experiments were carried out using training datasets with targets of all classes and test datasets with targets and confusion samples. Therefore, it is possible to determine the CC (amount of Correct Classified samples taken from the target test samples) and the FAR (False Alarm Rate, i.e. the amount of confusion samples that have been classified erroneously as one of the targets). The CC and FAR are given in % for different parameter selections related to the tested methods. In common we are interested in a high classification rate CC at low FAR, but also the so-called closed-world performance, i.e. the best classification rate without consideration of the FAR, is a marker for the classifiers performance.

5.1 QinetiQ Data Catalogues

A dataset provided by QinetiQ in the context of NATO SET-053 was used for the experiments. It contains 4006 images subdivided into 9 classes from A to I. Each class is subdivided into a training set consisting 335 different target aspects and into a test set consisting of 110 test samples. The complex-valued images of size 150x100 depict single targets. However, the target positions vary from image to image. As a fixed target position is a prerequisite for the classifier, 64x64 windows are selected in a pre-processing step that contains gravity-centered targets. The investigations are carried out with images alike depicted in Figure 3. These are span images degraded to 32x32-pixel size, i.e. the polarimetric information was only used to improve the SNR. The four classes A, B, D and G represent the desired targets. The other five classes provide confusion objects. After the classifier training, the test samples of all nine classes are classified.

In Figure 4 the resulting ROC (Receiver Operator Characteristic) curves concerning our previous heuristic method are given. The related CC and FAR values are determined depending on two parameters. – The family of curves is parameterized by the reject threshold d_{min} and the curves itself are determined by varying the parameter σ of the RBF kernel. The closed-world performance (the best classification rate without taking the FAR into account) is about 90.91%. In addition, a low FAR of 7.8% is possible with a CC of 77.05% (also a FAR of 16.15% is given at CC of 86.59%).

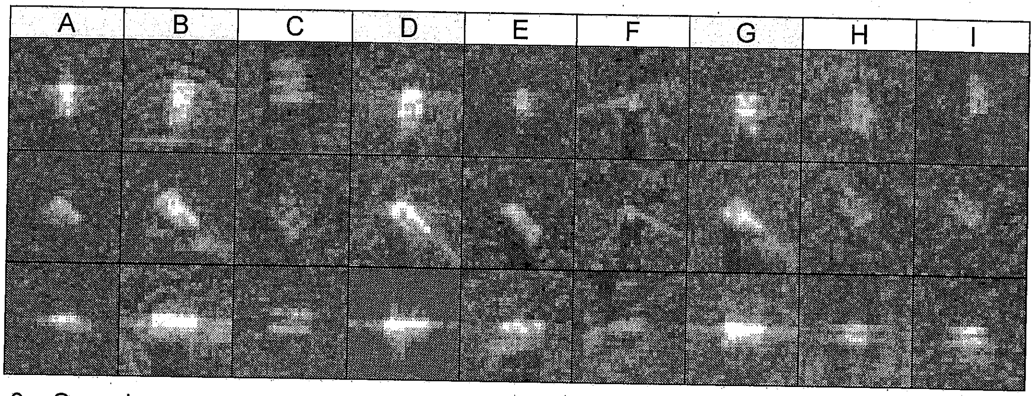

Figure 3. Span image samples in dB of the classes A to I (one class per column) of the QinetiQ SAR dataset, Targets A, B, D, G; Confusion objects are all samples of the classes C, E, F, H, I

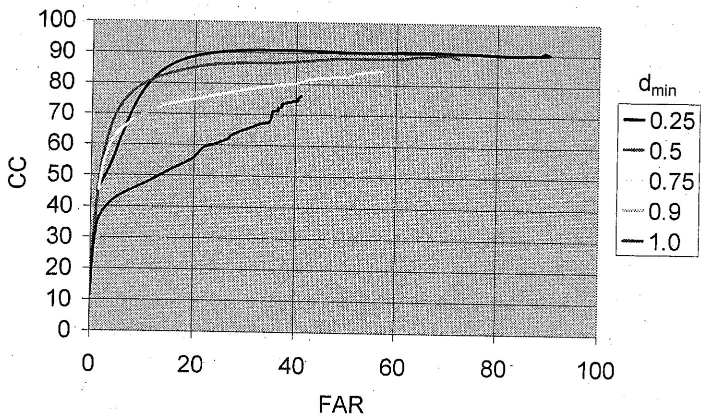

Figure 4. ROC curves for the heuristic method applied to the 4 target classes (A, B, D, G) and the confusion classes (C, E, F, H, I) at different d_{min} levels, classification rate *CC* and *FAR* in %

The experiments with the method based on the 1-class SVM as membership assessor applied to the original data result in poor classification rates. The closed-world performance drops to 81.59%. This result is essentially lower than the 90.91% we got for the heuristic method. The results further indicate that it is impossible to achieve simultaneously a satisfactory classification rate and a sufficiently low FAR.

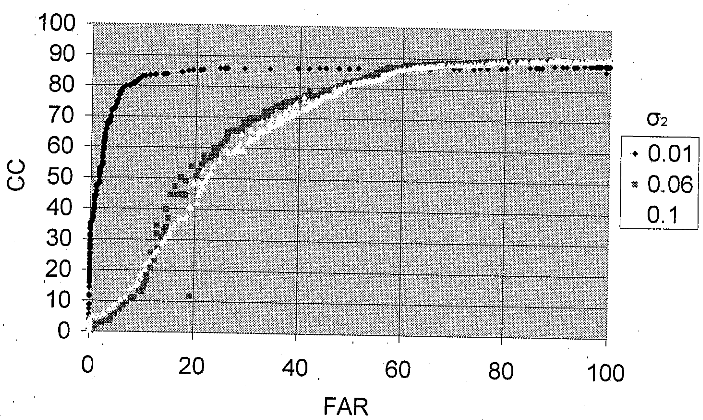

Figure 5. ROC sets of SVM21 parameterized by σ_1 and *TOL* applied to the 4 target classes (A, B, D, G) and the confusion classes (C, E, F, H, I). Different σ_2 levels are displayed, *CC* and *FAR* in %

In Figure 5 the results of our experiments with the novel SVM21 approach are presented. The RBF-kernel parameter σ_2 of the features generating classifiers is defining the family of curves. The curves itself are obtained by concurrently varying the parameter σ_1 of the membership assessor and the reject threshold *TOL*. The closed-world performance is about 90.23%. But at low FARs it is even better than the heuristic method, e.g. we obtain 7.44% FAR and 80.23% CC.

5.2 MSTAR Data Catalogues

Additional investigations have been carried out with the MSTAR public target dataset. Ten classes are taken into consideration. In an operational environment this is a lower limit. The dataset consists of 3671 training and 3203 test samples. The depression angle is 17° for the training data and 15° for the test data samples. Normalized and gravity-centered targets have been processed in 64x64 pixel windows as training and test catalogues.

The closed world performance for the SVM21 is at 98.00% for the 10-class problem. The classification quality CC depends on the three parameters σ_1, σ_2, and TOL. In Figure 6 CC is given by taking the maxima with respect to TOL for each σ_1, σ_2 parameter selection. It can be seen the robustness of CC relative to σ_1 variations.

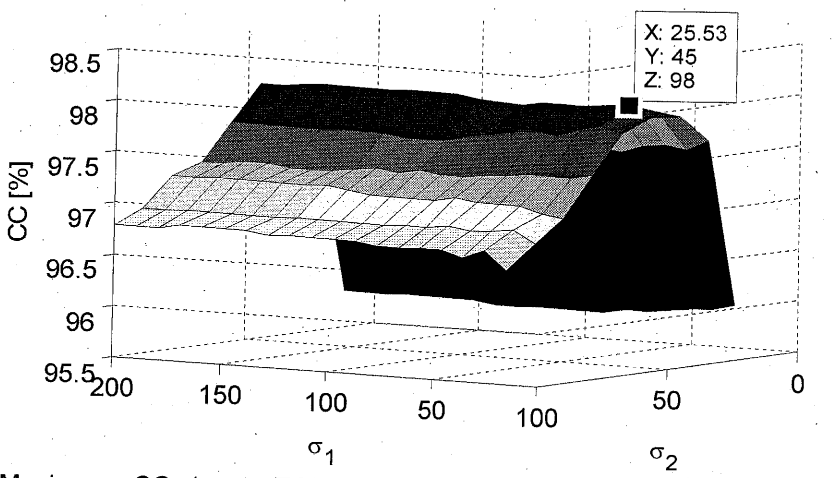

Figure 6. Maximum CC (w.r.t. TOL) values of SVM21 for the MSTAR 10-class problem, visualization of the parameter dependence, closed world performance at 98.00% (CC is the z axis)

The confusion samples are taken from the MSTAR clutter scenes (1st set). From each of these 50 scenes the 150 most significant samples have been chosen. They are pre-processed like the target samples (centering and normalizing). The ROC set given in Figure 7 (overview at the left side and details at the right) is computed taking the 10 target classes and those 7500 confusion samples into account.

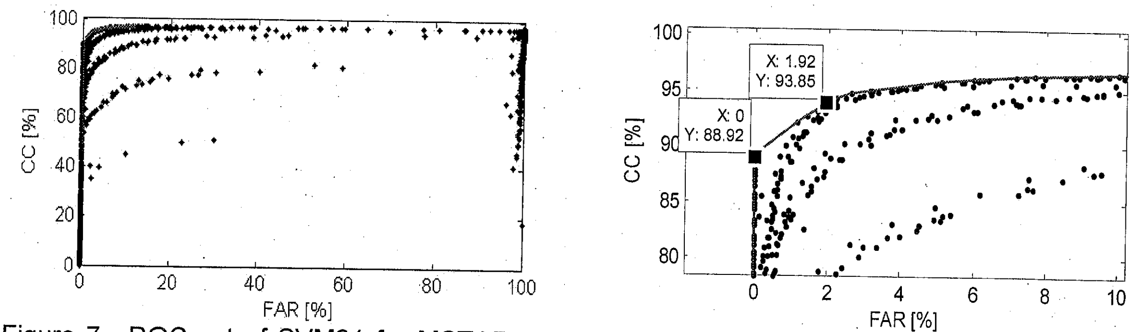

Figure 7. ROC set of SVM21 for MSTAR 10-class problem with 7500 clutter samples taking into account, overview at the left side and details at low FARs at the right (FAR=x, CC=y axis)

The classification rate drops to 88.92% at the lowest FAR (0.00%). In spite of the necessary normalization this is an acceptable result.

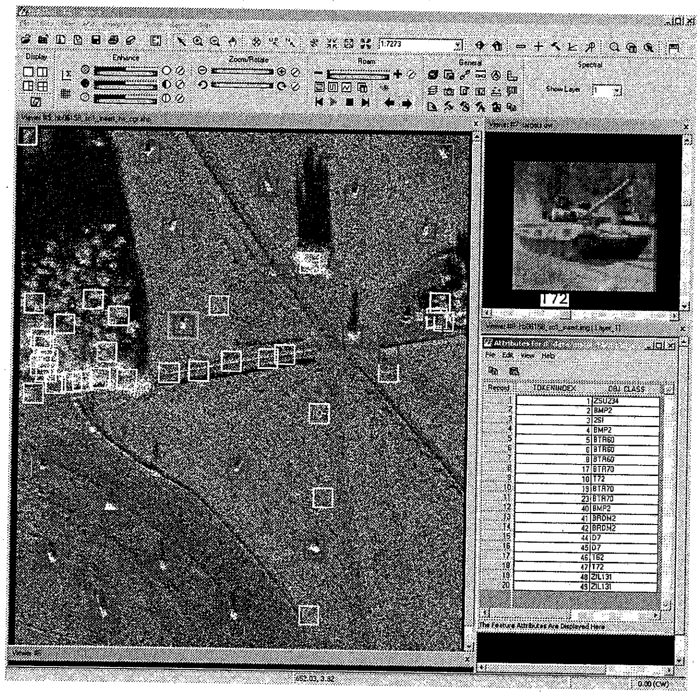

Figure 8. ERDAS user interface with classification results of applied on MSTAR 10-class problem, target vehicles inserted into a clutter scene, accepted (red), rejected (yellow), and the selected (green) object

In Figure 8 an example of our ATR software demonstrator integrated in ERDAS is depicted. The SAR scene is presented in the main window with the classification results. Rejected objects are marked with yellow boxes. Accepted objects are signed with red boxes. The user has selected one object (green box) that is displayed in the upper right window indicating the classification result. A list of the detected targets and further feature attributes can be displayed in the lower right window.

6 CONCLUSION

A processing chain of screening and classification is presented. The novel SVM21 approach for classification enabling the rejection of non-trained objects has been tested for several datasets. At low FARs it yields better results as our previous heuristic method. The classification quality is robust against variations of the parameter σ_1 in contrast to the poor results of 1-class SVM without a pre-classifier, because a prerequisite is an equal scale of all membership assessments. Furthermore the SVM21 is robust against clutter objects and consumes a moderate amount of computational effort.

The influence of further SAR Parameters and SAR operation modi should be investigated. Other pre-classification concepts should be studied as well.

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