SAR Image Segmentation with GMMs

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Abstract

This paper proposes a new approach for Synthetic Aperture Radar (SAR) image segmentation. Segmenting SAR images can be challenging because of the blurry edges and the high speckle. The segmentation proposed is based on a machine learning technique. Gaussian Mixture Models (GMMs) were already used to segment images in the visual field and are here adapted to work with single channel SAR images. The segmentation suggested is designed to be a first step towards feature and model based classification. The recall rate is the most important as the goal is to retain most target's features. A high recall rate of 88%, higher than for other segmentation methods on the Moving and Stationary Target Acquisition and Recognition (MSTAR) dataset, was obtained. The next classification stage is thus not affected by a lack of information while its computation load drops. With this method, the inclusion of disruptive features in models of targets is limited, providing computationally lighter models and a speed up in further classification as the narrower segmented areas foster convergence of models and provide refined features to compare. This segmentation method is hence an asset to template, feature and model based classification methods. Besides this method, a comparison between variants of the GMMs segmentation and a classical segmentation is provided.

1 Introduction

The purpose of segmentation is to give meaning to an image and facilitate further analysis. In the particular case of the MSTAR dataset, two types of segmentation are observed. The segmentation can focus on the target only or on both the target and its shadow. It is challenging to segment SAR images, as there are no sharp edges to delimit the target or the shadow from the background. The presence of noise with a high standard deviation makes the choice of a direct threshold difficult as either the target will not be entirely detected, or some background will be falsely detected. Most of the segmentation methods already implemented try to isolate the target only [1] [2]. After going through some pre-processing, the segmentation is done using thresholds. Some methods [3] enhance the precision of the method by applying an adapted threshold based on the contour of the previously found target. It is hard to evaluate and compare the segmentation results as there is no publicly available official ground truth. One manual segmentation method was proposed as a segmentation reference. It includes manual segmentation by an analyst followed by a quality control check by a supervisor [4]. However, the result of this segmentation is not publicly available and would be labour intensive to reproduce. Another ground truth was proposed by simulating the projection of the 3D CAD target's model on the ground in a similar configuration to the MSTAR dataset to estimate the contour of both target and shadow [5]. This is what we will use to evaluate the proposed segmentation method. To our knowledge, no existing paper gives the complete set of precision, recall and dice score with this ground truth.

Unlike previous methods where the focus was on achieving a good segmentation by the usual standards such as a high Dice score, the main objective here is to ease the classification process. The objective is to retain all possible features from the target while discarding the noise. This improves all types of classification methods. Indeed, the templates are lighter, the comparison of features is faster with refined features and the convergence of models is boosted with noise reduction. This segmentation can also prevent mismatches between features of the target and the clutter as it will be suppressed through segmentation. The main evaluation of our method will be through the recall rate, while providing the other classical rates, to assess the retention of the target area. However, the area around the target can be misclassified as the target because of the recall rate focus. This is balanced by the additional information the multipath near the target can give. This segmentation fulfills its purpose if the classification does not rely on shape recognition. We made this assumption as we believe that contour shapes do not strongly characterise SAR targets.

Firstly the SAR database and segmentation ground truth used to evaluate the method are presented. The whole segmentation process is then described, explaining the acquisition of a background GMM model and the actual process of GMM segmentation. Finally a comparison between different segmentation techniques is given.

2 Dataset

2.1 MSTAR dataset

The public MSTAR dataset [6] was developed by the U.S. Defense Advanced Research Projects Agency (DARPA) and the U.S. Air Force Research Laboratory (AFRL) in 1995. It has a 0.3m$\times$0.3m resolution and was obtained under HH (Horizon-

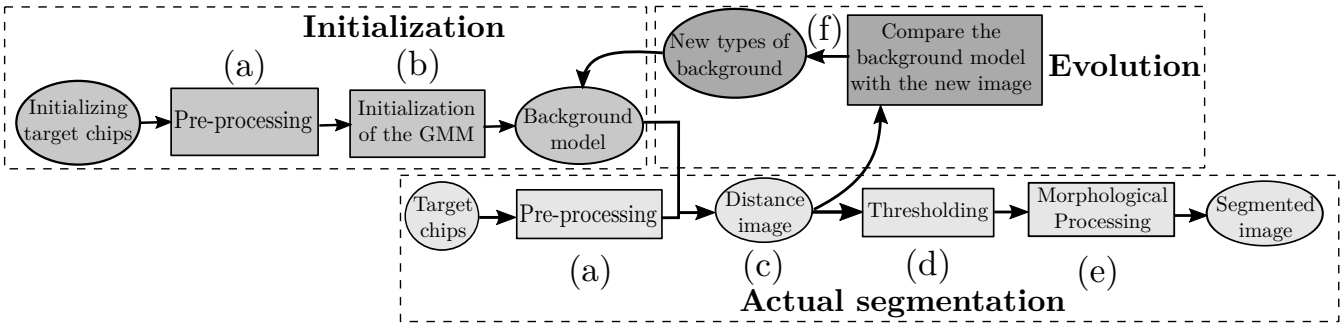


Fig. 1: Pipeline of the segmentation process

tal Horizontal) polarisation in X-Band. There are nine targets. The low resolution and blurred edges make it a challenge to get a precise segmentation.

2.2 Segmentation ground truth

The segmentation ground truth used for our method's evaluation is based on the findings of [5]. The 3D CAD model of the target is orthographically projected with the same orientation displayed in the image. The result is a 2D segmented image. The exact position of the segmented objects is adjusted to best fit the images using a correlation criterion. There are 33 sequences available and segmented with this method out of the 44 sequences of the MSTAR dataset from different targets and different depression angles. All 33 will be used to evaluate the segmentation results of the presented method.

3 Technical description of the segmentation

The presented segmentation method relies on the GMM machine learning technique. The major steps of the method can be seen in Fig.1. Firstly, the initialisation (in green in Fig.1) gets a model of the background. To initialise the background GMM model, a few target chips are chosen and processed to extract a GMM characterisation of the background. Then, the actual segmentation (in blue in Fig.1) can be done by comparing the background model to the image to segment. This gives a distance image representing the likelihood of the area to belong to the background. The final image is obtained after thresholding the distance image and some further morphological processing. The remaining areas are the ones the least likely to be part of the background, namely the target in the foreground. The algorithm can work without evolution (in yellow in Fig.1), however adding a learning phase makes it more accurate as the background is not the same throughout each sequence. The background model integrates new types of background as well as discarding the GMMs not representative any more of the current background along the sequence of images.

3.1 Choice of the initialising target chips

The first step consists in choosing the images that will be used to initialise the background. We choose few images from the beginning of the sequence rather than along each sequence. The variety of GMMs fitting the background at each stage is achieved along the sequence by making the model evolve.

3.2 Data pre-processing

Different pre-processing were tested in order to obtain the best segmentation. The objective of the pre-processing, (a) in Fig.1, is to reduce the noise without blurring the contour of the target. The choice of the pre-processing method was done empirically. The GMM segmentation was applied after the different pre-processing methods on the images where the classical segmentation methods failed the most, mostly because of a change of background. We evaluated the segmentation on the recall rate and dice score of the specification on those images. Two bilateral filters and a median filter is the combination that gives the best results. This pre-processing was compared with other pre-processing methods such as mean filtering, contrast stretching or histogram equalisation.

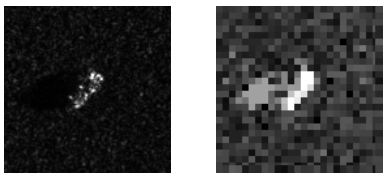
3.3 Adaptation of the GMM to the single channel SAR image

The GMM is a probabilistic model made from a combination of Gaussians to represent data that could be subdivided in different subsets. It has already been used to segment visual images [7]. In our case, the GMMs represent different areas of the images and follows Eq.1. The background is modelled instead of the target as it has less variance and is more predictable.

$$\begin{cases} \mathcal{B}(\theta_1, ..., \theta_n) & = \{GMM_1(\theta_1), ..., GMM_n(\theta_n)\} \\ GMM_i(\theta_i) & = \sum_{j=1}^{K} \phi_j * \mathcal{N}_j \end{cases} \quad (1)$$

where $\mathcal{B}$ is the background model, GMM_i is the i_{th} GMM composing the background model. Each GMM is made of K Gaussians $\mathcal{N}_j$ with a weight ϕ_j over an observed intensity distribution θ_j.

Images in the coloured visual spectrum have usually three channels (red, green and blue). Multipolarised images could be an equivalent for SAR images but different polarisations were not available in the MSTAR dataset. The intensities of a group of pixels, a 10×10 pixels square, are used as the distribution to be modelled by a GMM. As a group, the intensities balance the lack of information due to the single channel and limit the impact of the noise. The initialisation of the background model (b) in Fig.1 begins by estimating the GMM parameters using a K-Mean algorithm. This algorithm is quick and gives a first idea of the clustering of the data in different Gaussians. Start-



(a) Original image **(b)** Distance image

Fig. 2: Distance image between the extracted GMMs and background model

ing directly by expectation-maximisation (EM) is likely to fall in a local minima. The EM gets a more accurate estimation of the GMM parameters. As the background occupies the most space in the images, the GMMs related to the background are the most frequent ones. The most similar GMMs are grouped together to determine their prevalence. The similarity is established using the Kullback-Leibler (K-L) divergence based on Gaussian approximation [8] written in Eq.2.

$$\begin{cases} dist(GMM_i, GMM_j) & = \min\limits_{\forall m \in S_i, \forall n \in S_j} KL(\mathcal{N}_m, \mathcal{N}_n) \\ KL(\mathcal{N}_m, \mathcal{N}_n) & = \ln\left(\frac{\sigma_n}{\sigma_m}\right) + \frac{(\mu_m - \mu_n)^2 + \sigma_m^2 - \sigma_n^2}{2\sigma_n} \end{cases} \quad (2)$$

where S_i is the number of Gaussians in the GMM_i, N_m is the m_{th} Gaussian distribution $\mathcal{N}(\mu_m, \sigma_m)$ of the GMM_i.

If the divergence is below a threshold, the GMMs are considered similar and the weight representing the occurrence of these GMMs is updated as the sum of the two GMMs weights. The GMMs selected to model the background are the 80% GMMs with the heaviest weight. They are likely to represent the background as one target only occupies around 2% of the image space in the MSTAR dataset.

3.4 Segmentation

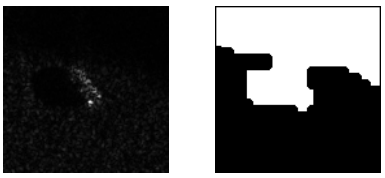
The segmentation is a two phases process. The distance image, (c) in Fig.1, is computed using the background model previously obtained and the new image. It is then thresholded, (d) in Fig.1, to obtain the binary segmented image.

3.4.1 Distance image

The image is divided in 10×10 square patches and a GMM is deduced from each patch. The distance image in Fig.2 links the pixels' intensity to the K-L divergence as in Eq.2 between the GMMs from the background model and the GMMs found in the image to segment. Each patch's new intensity is the minimal divergence found between the new GMM and the background model GMMs. A logarithmic filter stretches the lower intensities and makes the choice of the threshold more accurate.

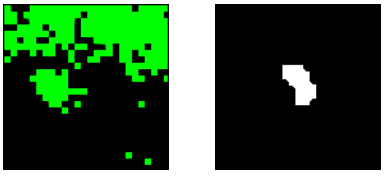
3.4.2 Thresholding

The choice of the threshold (d) in Fig.2 relies on the assumption that the target covers a small part of the image. The threshold is chosen so that only the brightest part of the image is retained. A larger threshold could be used as the post morphological processing would suppress the majority of the false alarms but some false alarms could still remain.



(a) Original image **(b)** Segmentation result

Fig. 3: Result of the segmentation without evolution



(a) GMM candidates **(b)** Segmentation with evolution

Fig. 4: Location of the GMM candidates and result of the segmentation with evolution

3.5 Morphological filtering

Morphological filtering, (e) in Fig.2, is essential to correct the first results of the segmentation. The target can be split up after the segmentation process in different parts and the dilation helps reconnecting them. However, the dilation makes the detected target larger and swells the misclassified background parts. The dilation is thus followed by an erosion. At this stage, the target is detected and its shape is well approximated but there are still false positives. Most are removed while areas below a specific surface are suppressed. An optional step is to add a dilation boosting the recall rate. As the target is now the only positive area, a dilation adds to the detection areas surrounding or on the target.

3.6 Evolution of the background model

Along the sequence, the background can change and if the background model keeps only the original GMMs, the new background types will not be represented by the model and lead to false positives as shown in Fig.3b. To take into account this problem, the set of background GMMs we saw fit for describing the background at the beginning of the sequence evolves, (f) in Fig.2. The evolution consists in the removal of the out of date GMMs and the introduction of the GMMs fitting the new background types. The evolution step work for the images when they are following each other in a sequence. The criteria for a GMM to be kept or added to the background model is consistency across several images. The weight of each GMM type is computed as during the initialisation in section 3.3. Only the GMMs whose weight is over a certain threshold are kept. The GMMs surrounding or located on the found target are removed as they can be related to the target. To do so, the location of the new GMMs in Fig.4a is compared to the dilated segmented image shown in Fig.4b. The GMMs in the positive area will not be considered for background modelling. If the GMM satisfies these criteria on 5 following images, it is included in the background model, otherwise the GMM is removed from the model. One can see the

Segmentation method	Precision	**Recall**	Dice Score
Technique 1	17 %	71 %	28 %
Technique 2	63 %	78 %	69 %
Technique 3	47 %	**88** %	61 %
Technique 4	62 %	55 %	58 %

Table 1: Segmentation results: Technique 1: Basic GMMs. Technique 2: GMMs with evolution. Technique 3: GMMs with evolution and morphological processing. Technique 4: Pre-processing and thresholding [9].

improvement on the result of the segmentation by comparing Fig.3b and Fig.4b to the original shown in Fig.3a.

4 Results

The main objective of this segmentation is to detect the target as a whole even if the precision decreases. False negatives are more damaging for further processing and classification than false positives. Indeed, the clutter having none of the target features will be discarded at the classification stage whereas a part of the target missing could mean the loss of a crucial feature. This is why the recall rate is used as the important criterion to evaluate the performance of our segmentation method.

4.1 GMM technique

The very low rate of 17% of precision of technique 1 in Table 1 shows that the basic GMMs technique is prone to false alarms. This endorses the overall change of the background throughout the sequences and that the background model should be updated accordingly. This hypothesis is confirmed looking at the 63% precision rate achieved once the evolution process is introduced as per technique 2. The number of true positives increases with the recall rate. There can be more true positives because of the dilation only if the previously detected area is already on or near the target. The difference between the recalls of techniques 2 and 3 from 78% to 88% in Table 1 confirms the previous detection was rightly located. As can be seen in Table 1 from the precision and recall rate of techniques 2 and 3, the last morphological step is a trade-off between precision and recall. With the highest recall rate, technique 3 is favoured.

4.2 Comparison with other techniques

Technique 4 in Table 1 is used as a preliminary step to several classification methods [9] [2]. This method consists of an histogram equalisation followed by a mean filter as preprocessing. A constant intensity threshold is then used to remove the pixels with a low intensity. The median of the intensity of the pixels remaining is used as a second threshold. Usually the target is well detected even if it is in several pieces. However, the background is detected as well. These results are shown by a comparable precision of the GMM technique 2 of 62% seen in Table 1 but a much lower recall rate of 55%.

5 Conclusion and future work

The presented technique has a high recall rate of 88% satisfying the objective of a loose segmentation keeping most of the target and its features while removing the background to ease further analysis of the image. We observed a higher recall rate for this segmentation method than for other techniques that we tested. This can be interesting for feature or model based classification methods with a heavy computation load but that requires a detailed description of the target. Further work is considering several processes to increase the precision of our algorithm. The dilation could be done with a kernel whose size varies with the probability of the area to contain a target using the distance image. A fine edge detection could be added around the border previously found with the segmentation to get a more accurate contour of the target. The segmentation could also be extended to detect both the target and its shadow. Either the threshold method could be changed to cluster the histogram in three classes or a shadow model could be created as the presented background model.

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