Segmenting Shadows from Synthetic Aperture Radar Imagery
Using Edge-Enhanced Region Growing

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ABSTRACT
An enhanced region-growing approach for segmenting regions is introduced. A region-growing algorithm is merged with stopping criteria based on a robust noise-tolerant edge-detection routine. The region-grow algorithm is then used to segment the shadow region in a Synthetic Aperture Radar (SAR) image. This approach recognizes that SAR phenomenology causes speckle in imagery even to the shadow area due to energy injected from the surrounding clutter and target. The speckled image makes determination of edges a difficult task even for the human observer. This paper outlines the edge-enhanced region grow approach and compares the results to three other segmentation approaches including the region-grow only approach, an automated-threshold approach based on a priori knowledge of the SAR target information, and the manual segmentation approach. The comparison is shown using a tri-metric inter-algorithmic approach. The metrics used to evaluate the segmentation include percent-pixels same (PPS), the partial-directed hausdorff (PDH) metric, and a shape-based metric based on the complex inner product (CIP). Experimental results indicate that the enhanced region-growing technique is a reasonable segmentation for the SAR target image chips obtained from the Moving and Stationary Target Acquisition and Recognition (MSTAR) program.

Keywords: segmentation, evaluation, recognition, edge detection, synthetic aperture radar, metrics

1. INTRODUCTION
One of the main problems with Synthetic Aperture Radar (SAR) imagery is that an image pixel may contain energy reflected from adjacent objects causing noisy speckled-filled imagery. Even in the SAR shadow area where no energy return should be expected, energy from adjacent target and clutter areas spill over into the shadow area causing a speckled shadow area. The noisy shadow makes edge detection difficult. Even for a human observer, the edge may be difficult to locate. A second problem with the SAR imagery is that no sufficient model for the exact edge location exists making evaluation of the results difficult. The focus of our recent work is overcoming these two problems by providing a segmentation algorithm for the SAR shadow area and by providing an approach to evaluating the segmentation results.\textsuperscript{1,3} To solve the problem of noisy SAR images, propose an edge-enhanced region-growing algorithm is proposed for segmenting the SAR shadow region. To solve the problem of evaluation, a tri-metric inter-algorithmic approach is proposed.\textsuperscript{4}

The experimentation for this paper was limited to using SAR target chips provided by the Moving and Stationary Target Acquisition and Recognition (MSTAR) program sponsored by the Defense Advanced Research Projects Agency (DARPA) and the Air Force Research Laboratory (AFRL). Sample target chips as shown in Figure 1. are SAR images of a T72 tank at different orientations. Each chip is guaranteed to have a target, shadow and clutter region. First, using these target chips, the difficulty that a human observer has with manual segmentation is discussed. Manual segmentation is followed by a section introducing the auto-thresholding approach based on a priori knowledge of the MSTAR SAR target chips. Then the last segmentation algorithm is introduced which is the region-grow technique. All three algorithms are then compared using a tri-metric inter-algorithmic evaluation.

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Figure 1. MSTAR T72 target chips illuminated from various angles illustrating target, shadow, and clutter regions.

Figure 2. The edges obtained from several attempts at segmenting a single T72 SAR shadow region.
2. MANUAL SEGMENTATION

MSTAR T72 tank target chips as shown in Figure 1 are used to demonstrate and test the shadow segmentation algorithms. Attempting to manually segment the shadow area of an MSTAR target chip reveals that a human observer has difficulty trying to determine the edge for a target chip. This difficulty is illustrated in Figure 2 where several attempts to manually segment a T72 target chip yields different results. It has been illustrated in an earlier paper\(^2\) that the more speckled the image, the greater the variance for human observers attempting to segment the shadow region. The variance was illustrated using an evaluation metric based on percent-pixels different between manual segmentation results. This variance is an indication of how accurate an image can be segmented. For the particular target chip shown in Figure 2, the main variance occurs in the the gun and barrel regions as well as the region adjacent to the target. Additional energy from the adjacent target region mixes with the shadow region causing an area of mixed shadow and target. Likewise, for the gun and barrel next to the clutter regions, the thinness of the gun and barrel cause a slightly brighter shadow due to additional energy from the adjacent clutter areas.

![Figure 3. A smoothing filter is applied to reduce the gray variance in the shadow region.](image)

3. AUTO-THRESHOLDING BASED ON A PRIORI KNOWLEDGE

If a system has a priori knowledge about the imagery being segmented, then in some cases, that knowledge can be used to assist the automation process. For instance the data being segmented to examining target chips which are guaranteed to have a target region, shadow region, and clutter. Also knowledge exists about the general clutter background, general target size and thus the general area of the target and expected shadow size at different azimuths. Using this knowledge an auto-threshold approach to segmentation can be created and applied to all the target chips in the set.

The first step to auto-thresholding is to custom design a filter kernel based on knowledge of the clutter statistics to allow filtering of the target chips. The filtering is needed in order to change the speckled regions to smoother tones as illustrated in Figure 3. The filter used has a low pass characteristic as shown in Figure 4. Low pass filtering results in a tradeoff when reducing the speckle. The speckle is reduced but so is high frequency edge information. Therefore, the art of creating a filter kernel requires tuning to reduce the speckle but only enough to maintain some edge information.

The second step to auto-thresholding is to locate a point in the shadow region. Image intensity, \(I(x,y)\), at any given \(x,y\) point in the \(N\) by \(N\) MSTAR target images have been scaled to range from a gray value of 0 (black) to
**Figure 4.** Frequency response of smoothing filter applied to reduce the gray variance in the shadow region.

**Figure 5.** Shadow Area versus threshold for MSTAR target chips shown in Figure 1.
To locate a point in the shadow region, the averages of subregions are compared until the one of lowest average is found. Thus, given a small square of size \((2K + 1)^2\), the average value at a \(x, y\) point is

\[
I_{\text{ave}}(x, y) = \sum_{i=x-K}^{x+K} \sum_{j=y-K}^{y+K} I(i, j) \tag{1}
\]

where \(K \leq x \leq N - K, K \leq y \leq N - K\) and

\[
K < \frac{N - 1}{2}. \tag{2}
\]

A shadow point \(x_s, y_s\) is then determined as

\[
(x_s, y_s) = \arg\min_{K \leq y \leq N - K} (I_{\text{ave}}(x, y)). \tag{3}
\]

The third step is the threshold selection step. Using a priori knowledge of the shadow area, a threshold can be determined iteratively. For the target chips shown in Figure 1, the shadow area versus threshold plot is obtained as shown in Figure 5. It needs to be noted that selecting a single threshold does not guarantee a shadow region segmentation since a vertical line drawn on Figure 5 can miss some of the target chips. However, selecting a horizontal line guarantees some shadow segmentation as long as a maximum is avoided. Also, the a priori knowledge about desired shadow area provides an automatic threshold selection. The actual value of the shadow area can actually be a range of values and still be within the variance of the manual segmentation results. In one experiment, shadow areas ranged from 871 to 1401. Choosing a constant value in this range is a quick way to segment without requiring precise a priori knowledge. For example, choosing threshold as a function of a fixed area yields different threshold values and reasonable shadow areas as shown in Figure 6.

### 4. REGION GROWING APPROACH TO SEGMENTATION

The shadow area segmentation based on auto-thresholding is not fully sufficient. Loss of some edge information due to the low pass filtering and the variations in the texture even in the shadow region suggest a more sophisticated approach. It is also desirable to have an approach that is less dependent on a priori knowledge. Recently, a region growing technique to improve the segmentation of SAR shadows was introduced by Wilson and Power.

#### 4.1. The Edge-enhanced Region Growing Algorithm

A region growing algorithm attempts to find a closed, simply connected region by growing outward from a known point and including inside the region all pixels which meet certain criteria. For a region with unknown shape, the stopping criteria may be either global, such as total area enclosed, or local. In this latter scheme, the growth will continue until the criteria is no longer met. For example, a selected number of consecutive threshold failures in a single direction would serve as a stopping point flag at some pixel in that particular direction.

For combining global shape knowledge with local amplitude criteria, one method is to include edge detection as one of the stopping criteria in the region growth area. Prior to the beginning of the region growth, the image was subjected to edge detection; due to the noise and blurring in SAR imagery, the edge detection results gave a level of confidence figure, rather than the binary decision output common to most methods. In this effort, a confidence level of 1.0 was assigned to the pixel with the highest probability of being on an edge. The minimum confidence value was 0 for at least 75 percent of the pixels in the image, with the remainder assigned values between 0 and 1.0.

The edge confidence was then used along with the traditional growth stopping criteria to allow for a new reason to stop, i.e. the edge of the region has already been encountered. Such an additional stopping criteria allows robust growth in images with amplitude variance not only in the shadow itself, but also in the background. This tolerance of background variation is very important when considering that SAR shadows are blurred and do not generally have sharp edges, meaning that the outer portion of the shadow will contain some energy from the neighboring, fully illuminated pixels. The bleed-over of energy, or lack thereof, could force the region to stop growing too soon in an area with a bright background, but allow it to grow too far past the real shadow boundary into a darker portion of the background elsewhere in the image. This effect was the primary cause of the ragged edge-shaped region in Figure 7.
Most importantly, though, the second stopping criteria forms a more secure border than traditional amplitude thresholds, since the edge confidence was found using a larger neighborhood. This allows the use of looser amplitude threshold criteria, resulting in more of the real shadow included, and a smoother outer boundary in all images tested so far. The amplitude threshold difference between the region-grow only method and the edge enhanced region-grow method was almost 10 percent. The smoother shape in Figure 8 demonstrates how the additional input and looser threshold criteria allows the shadow region to grow into a more "natural" shape.

4.2. Subjective evaluation of Region Grow Results

The results of using the region growing technique without edge enhancement are shown in Figure 7. The gun barrel is missing and the edges are very rough. By adding edge-enhanced stopping criteria, an improvement is shown in Figure 8 whereby the gun barrel is extracted. Up to this point, the segmentation results have been evaluated subjectively. The next section uses an objective approach to evaluate the segmentation results.

5. TRI-METRIC INTER-ALGORITHMIC SEGMENTATION EVALUATION

To objectively evaluate the segmentation results, a tri-metric inter-algorithmic approach is used. Tri-metric refers to using three metrics instead of one to obtain a comprehensive evaluation. The three metrics being used include percent-pixels same (PPS), partial-directed hausdorff for omission errors (O-pdh) and commission errors (C-pdh), and the complex inner product (CIP) based metric. The partial-directed hausdorff (PDH) metric was introduced as two metrics O-pdh and C-pdh but for the target chips being evaluated in this paper, the values of O-pdh and C-pdh are similar, so the results are presented as one normalized PDH metric represented as

\[
pdh(\delta) = \frac{N_{K(h)}}{N_{REF}} = \delta
\]

![Figure 6](image-url)

Figure 6. The automatically thresholded shadow region based on a fixed area of 1075 pixels for the target chips in Figure 1.
where $N_{RF}$ represents the total number of edge points and $N_{R(K)} = \delta$ represents the total number of edge points within a distance of $\delta$ from the reference edge. This metric is dependent upon the edge being spatially correct. The PPS metric is a variant of the percent-pixels different (PPD) metric\(^2\) such that

\[
PPS = 1 - PPD.
\] (5)

The PPS metric is less sensitive than the PDH metric to spatial variations in the edge. The PPS is sensitive to changes in mass as it calculates the percent of mass that is the same between two cuts of the same region obtained from two different segmentation attempts. The third metric in this trio is the CIP metric which is sensitive to shape. The CIP metric\(^b\) is given as

\[
cep = \sum_{n=1}^{N} V_{n}^{1/n} V_{n}^{\phi/k}.
\]

Dividing by the edge vector length, $N$ restricts the CIP metric to a range of $0 \leq \epsilon_p \leq 1$. The complex vector $V_{n}^{1/n}$ is formed by placing the segmented edge on a complex plane. $V_{n}^{\phi/k}$ is the reference edge which is formulated as a 1-D variant of an amplitude-modulated phase-only filter. The PDH, PPS, and CIP metrics provide variational measures for changes in spatial edges, mass and shape respectively providing a more comprehensive evaluation than one is able to obtain from just using a single measure.

To complete the evaluation, the tri-metrics are combined with an inter-algorithmic approach. The inter-algorithmic approach compares segmentation results from various quality algorithms and if the variance is within an acceptable limit, then the segmentation is judged to be reasonable. This approach is necessary for sensor imagery where true knowledge about the edge location (known as "truth" data) does not exist. SAR images typically lack truth data.

**Figure 7.** Using region growing segmentation without edge enhancement produce ragged edge and gumless results.

**Figure 8.** Using region growing segmentation with edge enhanced stopping criteria.
when imaging a target due to variations in clutter, target dynamics, and limited models. Since real SAR imagery is used where the exact edge model is not known, the inter-algorithmic approach is a useful technique for evaluation. Previously, a baseline for comparison of various segmentation algorithms has been calculated using supervised manual segmentation. In this paper, the automated algorithms are evaluated by using the variance in two manual segmentation results as the baseline. The manual segmentation variance is compared to the variance calculated between each automated approach and a manual segmentation approach. The results are examined for consistency.
6. CONCLUSION

The results of this segmentation research demonstrate that the auto-thresholding and edge-enhanced region grow approach to segmenting SAR shadow from MSTAR target chips provide reasonable results. An advantage to the edge-enhanced region grow is that it is not dependent on the a priori information that is required for the auto-thresholding approach. The tri-metric inter-algorithmic approach to evaluating the segmentation results appear to match subjective assessment of the results.

REFERENCES


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Table 1. Results for evaluating the five segmentation results of Figure 9.