Detection of Camouflaged Vehicles for VHF-band SAR Based on Regression Models

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Summary

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Introduction

In this paper, a change detection algorithm (CDA) for ultra-wideband (UWB) synthetic aperture radar (SAR) imagery is presented.

- SAR Images Change Detection
  - SAR systems can provide high-resolution images at any time and weather conditions, which make them suitable for surveillance and defense applications;
  - In order to automatize this process, CDAs are employed;
  - Greater interest in these techniques in the last few years due to their flexibility and growing availability of SAR images.

Introduction

- Target Detection Problem
  - The challenge consists in detecting military vehicles concealed under foliage in multitemporal VHF band SAR images;
  - Usually a binary problem, where the operator is interested in discriminating targets from other structures.

- Main Goals
  - Automatically detect changes of interest in multitemporal SAR images with low computational cost;
  - False Alarm Rate (FAR) reduction is the ultimate goal.

Summary

Database Description

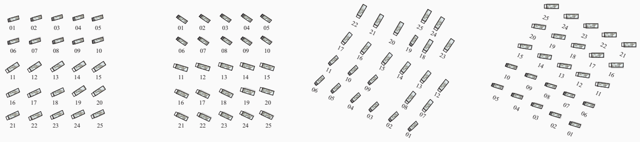
- Set of 24 SAR images from a forested area in northern Sweden. The images were acquired with the CARABAS-II SAR system, operating at 20-90 MHz and with foliage penetration capabilities;

- Each image covers an area of 3×2 km, where 25 military vehicles were concealed under vegetation in four different target deployments.

Figure 1. Vehicles concealed under foliage. Three classes have been employed: TGB11 (left), TGB30 (center) and TGB40 (right). Figure adapted from [1].

Database Description

The 24 SAR images can be divided into four different missions, associated with different target deployments, as can be seen in Figure 2:



(a) (b) (c) (d)

Figure 2. The different CARABAS-II missions and their respective target deployments: (a) Sigismund, (b) Karl, (c) Fredrik and (d) Adolf-Fredrik.

Summary

Logistic Regression

- Development of a change detection algorithm (CDA) based on Logistic Regression;
- Logistic Regression has become the standard method of analysis in many fields when the outcome is discrete, especially when it is assumed to be binary [2];
- Since the target detection only aims to discriminate targets ('1') from other structures or background ('0'), a Logistic Regression model can be properly trained to approach this problem.

Logistic Regression

- Given a known ground truth, features (covariates) that can statistically describe potential targets are selected;
- These covariates can be defined either qualitatively (e.g., flight heading) or quantitatively in the neighborhood of each pixel (e.g., pixel amplitude, mean, standard deviation and skewness);
- Proposed approach can overcome lack of pixel-based information, since the phase content has been removed from the images.

Change Image Generation

- Differencing
  - Given a monitored image (I_M) and a reference image (I_R) from the same area, a change image is generated through a pixel by pixel subtraction.

- Normalization
  - For each resulting pixel, subtract the mean and divide by the standard deviation of the entire image.

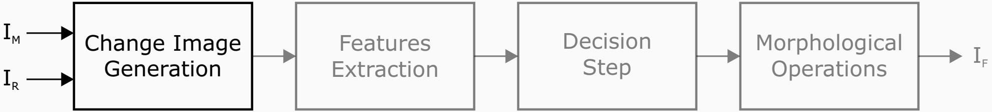


Figure 3. A change image is generated from two input images.

Features Extraction

Neighboring pixels are considered to statistically describe a region of interest, with a 5×5 pixels sliding window that is used to extract the following features:

- Pixel amplitude (x_1);
- Mean (x_2);
- Standard deviation (x_3);
- Skewness (x_4);
- Flight heading (x_5).

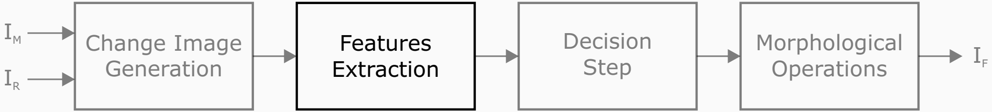


Figure 4. For each resulting pixel, five features are extracted in the neighborhood.

Decision Step

- LR Analysis
  - The decision process is then dictated by a multivariate logistic regression model described by:

$$P(Y = 1|x) = \pi(x) = \frac{e^{\beta_0+\beta_1 x_1+\cdots+\beta_5 x_5}}{1 + e^{\beta_0+\beta_1 x_1+\cdots+\beta_5 x_5}},$$

where $\pi(x)$ is the probability that each pixel represents a target. Given the binary nature of this approach, a thresholding is performed for $\pi(x) > 0.5$.

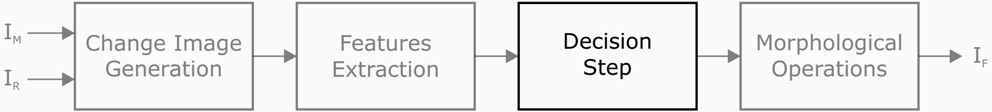


Figure 5. A threshold is applied based on a Logistic Regression analysis.

Morphological Operations

Applied to remove objects considered too small and to merge the ones that should form a single object. According to the known resolution, we have used a 3×3 erosion followed by a dilation operation, resulting in a final binary image I_F.

- Binary Mask
  - The positions of the remaining objects are compared to the ground truth, and the P_d and FAR are computed.

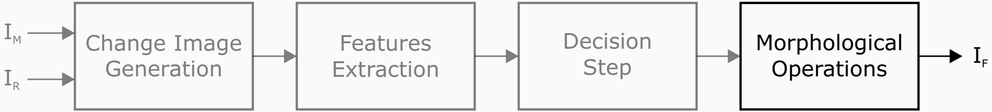


Figure 6. After morphological operations, a final binary change map is generated.

Training and Validation

The training of the multivariate logistic regression model considers 590 samples (pixels) per change image, where:

- 295 pixels are associated with targets according to the masks shown in Figure 7 (7 pixels per TGB11 and 15 pixels per TGB30 or TGB40);
- 295 pixels are associated with potential false alarms, such as fences and power lines.

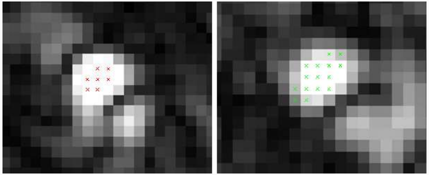


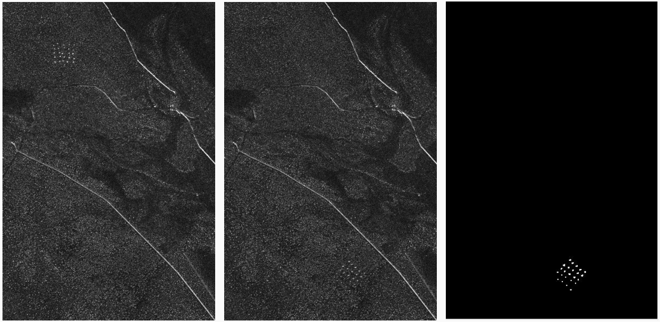
Figure 7. Proposed ground truth masks for training. The smallest vehicle (TGB11) considers 7 pixels while the truck-sized vehicles (TGB30 and TGB40) consider 15 pixels each.

Summary

Experimental Results

- The algorithm has been tested for the same 24 pairs of images presented in [1] through a K-fold cross-validation considering six iterations, i.e., the training is performed in 20 pairs of images and the test in four pairs at a time, until all the 24 selected pairs have been tested;
- The performance was evaluated in terms of probability of detection (P_d), which is the number of detected targets divided by the number of known targets, and FAR, which can be defined as the number of false alarms per square kilometer. In this paper, we obtained a P_d of 96.33% and a FAR of 0.28.

Experimental Results



(a) (b) (c)

Figure 8. Multitemporal input images and output image highlighting the changes: (a) reference image, (b) monitored image and (c) final change map.

Summary

Conclusions

- Experimental results show that the proposed CDA achieved a low FAR when compared to [1] (0.28 vs 0.67), while maintaining a high P_d (96.33% vs 96.5%);
- The proposed method does not require a stage for threshold selection, a great challenge for most CDAs;
- The CDA presents low computational complexity, since the change images were generated with a differencing technique and the training was performed with only 590 pixels per image (from a total of 6,000,000 pixels).

Summary

References

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