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Pattern Detection and Recognition in SAR Images

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***Abstract* — Synthetic aperture radar (SAR) is a powerful tool for remote sensing of the Earth surface. In the paper, several applications of pattern detection and recognition algorithms for extraction of information from SAR images are discussed. In particular, an idea of usage of optical flow techniques for automatic estimation of the moving target displacements from a sequence of single-look SAR images is proposed. It is shown, how this technique can be adopted for SAR imagery. In addition, it is demonstrated that local feature descriptors can be used for automatic SAR panorama creation without information about reference platform orientation. Finally, a problem of automatic target recognition is analyzed. It is shown, that a fusion of azimuth and range profiles of the ground target allows to achieve a competitive accuracy using quite compact feature vectors.**

Keywords* — *SAR, image stitching, moving targets, optical flow, target classification.

I. Introduction

Remote sensing of the Earth surface is a very wide area of research. In context of image formation, synthetic aperture radar (SAR) technique has a special place. It allows to obtain high-resolution imagery in real-time under various weather and lighting conditions [1]-[4].

In the last decade, SAR imaging from light-weight platforms and UAVs becoming more popular due to low operation and exploitation costs. However, motion instabilities can be properly accounted [5]-[6]. This is especially crucial for the high-resolution image formation. It is often required to apply both conventional motion compensation (MoCo) procedures together with specifically developed autofocus algorithms.

Fully focused images with a large number of SAR looks [4], [7] allow to distinguish types of textures, find the man-made objects on the ground, classify targets of interest, etc. There are a lot of examples of a successful information extraction from SAR images. In [8], example of sea ice classification is described. A proper analysis of image content allows to accomplish the classification in automatic way. Also a set of solutions were developed for automatic target recognition (ATR) task [9]-[10]. Another direction of research is related with textures in SAR images [11]-[12].

Analysis of modern trends in SAR research community gives a conclusion that pattern detection and recognition techniques are actively integrated into SAR systems. In the paper, we propose several contributions into this area of research. Firstly, it is proposed to track the moving target location in single-look SAR images using optical flow techniques [13]. It is described how to properly preprocess SAR images for good performance. Secondly, it is shown how to perform the SAR image stitching using local feature descriptors. Finally, we have analyzed the task of SAR ATR. Initial experimental results indicate that the proposed local feature representation allows to achieve good recognition accuracy using simple and compact data representation.

In Section II, developed road location and object shift estimation approaches are described. Section III describes the idea for automatic SAR image stitching using keypoint descriptors. Also the problem of SAR ATR is considered. Results of target classification are discussed.

II. Object Tracking for Moving Targets Analysis

This section contains the information about moving targets analysis problem and the proposed solution for tracking of the object shift using optical flow technique.

A. Moving Targets and Image Defocusing

It is known, that high-quality SAR images can be obtained only in the case of full motion compensation. However, the problem of moving object focusing still remains. Obviously, that in order to focus a moving target, both platform and ground target motion should be accounted.

Fig. 1 illustrates an example of single-look and multi-look images obtained with RIAN-SAR-X system developed at the Institute of Radio Astronomy [7]. Multi-look is a powerful technique commonly applied in SAR processing for speckle suppression [3]-[4]. After comparison of Fig. 1a and Fig. 1b one can observe that averaging of 65 looks gives significant quality improvement. In particular, textural blocks and fine details are visible in multi-look image. Let's consider similar example, but in the case of some ground movement. Fig. 1c contains an example of 1-look SAR image. One can observe the railroad, but the trace of train appears beyond it. This is a well-known effect on the object movement during SAR data acquisition. As a result, object signature appears to be shifted and defocused [14]-[15]. Obviously, that such shifts lead to different locations of the target trace in a sequence of single-look images. As a result, the train appears as smeared (blurred) object in resulting multi-look image (Fig. 1d).

Let's consider the problem of moving target indication (MTI) from signal processing point of view. The reason of shift and defocusing of target in SAR image is related with the fact, that the SAR matched filter is constructed for focusing of the static scene. In order to simplify the task, it is assumed that the target of interest is moving along straight line

$\vec{r}_T(t)=\vec{r}_T+\vec{\mathbf{v}}t$ with a constant velocity $\vec{\mathbf{v}}=(v_x,v_y,0)$. In this case the signal of the moving target is processed as a signal from some static point on the ground. This point is called equivalent static point (ESP). One can show that even in in the case of above mentioned movement of the object, the ESP trajectory will be described as the second order curve

$$V^2x_{eq}^2-2V_a(\vec{R}_T\cdot\vec{V})x_{eq}+(V^2-V_a^2)y_{eq}^2-(V^2-V_a^2)(R_T^2-H^2)+ \\ +(\vec{R}_T\cdot\vec{V})^2=0 \quad (1)$$

where (x_{eq},y_{eq}) are ESP coordinates, $\vec{R}_T$ is a vector to the ESP, R_T^2 is the range to the target, V_a,V is the platform and relative target velocities respectively. In order to estimate the target parameters (location and velocity components), ESP positions on a sequence of single-look SAR images should be known. Automatic solution of this problem is described in the following subsection.

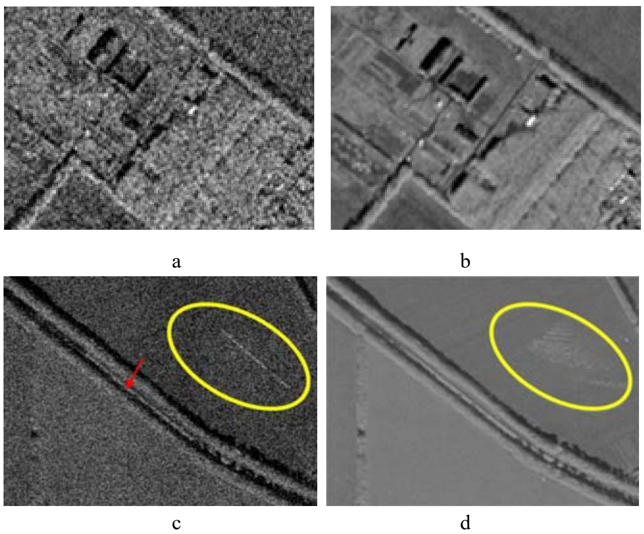

Fig. 1. RIAN-SAR-X images, 2m resolution (a – 1 look, b – 65 looks, c – 1 look with moving target, d – 65 looks with moving target)

B. *Estimation of Object Displacements in SAR Images*

Since at least two positions of ESP should be estimated for the MTI problem, a pair of single-look SAR images can be considered as an input.

In order to estimate shift of the ESP, we propose to utilize the optical flow (OF) technique [13]. This methodology is typically applied for the analysis of video sequences in optical band. The principle is based on the estimation of the apparent motion within the camera frame. One can show that it can described via so-called OF equation for a single image pixel

$$I_xu+I_yv+I_t=0, \quad (1)$$

where I_x,I_y are the horizontal and vertical image gradients, I_t is time gradient, i.e. difference between the frames, (u,v) are OF vector components. In order to solve (1), typically OF estimation is accomplished within local window around a target pixel as follows

$$\begin{bmatrix}\sum I_x^2 & \sum I_xI_y \\ \sum I_yI_x & \sum I_y^2\end{bmatrix}\begin{bmatrix}u \\ v\end{bmatrix}=-\begin{bmatrix}\sum I_xI_t \\ \sum I_yI_t\end{bmatrix}. \quad (2)$$

Two key assumptions are made within OF estimation procedure: pixel intensity preservation and camera frame preservation. In terms of SAR processing, adjacent SAR looks can be used as input for OF estimation. However, the problem is more complicated in this case. Firstly, speckle

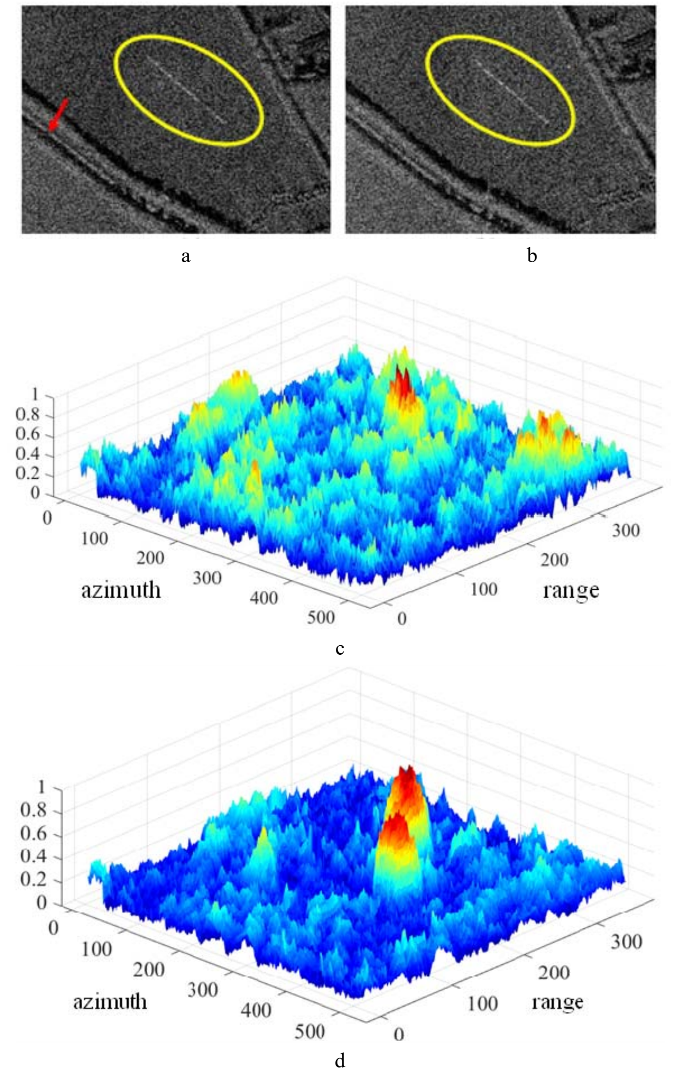

Fig. 2. SAR images and optical flow surfaces (a – SAR look 1, b – SAR look 2, c – OF surface without preprocessing, d – OF surface with preprocessing).

noise appears due to a coherent nature of raw data acquisition. Secondly, scattering properties might change with viewing angles (in different SAR looks). Finally, the real antenna pattern modulates the backscattered signal. Hence, this causes the pixel intensity modulation in obtained SAR images.

Fig. 2a and Fig. 2b contains a pair of SAR images with railroad and trace of the moving train. Fig. 2c illustrates the calculated OF surface using these images as input. One can observe a lot of false peaks with varying amplitudes. Also the region with the trace of the train is not clearly observed. The reason of such low performance of OF technique is related with above described factors.

In order to improve the target detection capability, we have developed a preprocessing algorithm. At first, the histograms of adjacent SAR looks are adjusted using the histogram of the multi-look image as a reference. Speckle noise is filtered [16] at the second step. Fig. 2d illustrates the result of OF estimation after application of the preprocessing precodure. One can see that the moving train signature is visible and the amount of false detections is significantly lower.

Developed algorithm for extraction of ESP locations was included into the framework for moving target parameters estimation. Fig. 3 illustrates the main steps

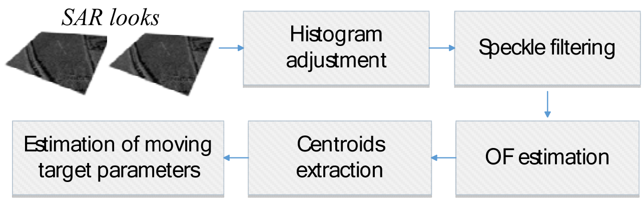

Fig. 3. Main steps of moving target parameters estimation framework.

Firstly, histogram adjustment and speckle suppression are applied for a pair of SAR images. After that OF magnitude is estimated in forward and backward directions. At the next step, global thresholds are applied to OF images. Finally, the ESP locations are estimated as a centroids of extracted blobs in binary images. As a result, this information is used for the unambiguous estimation of the moving target parameters [15].

III. Image Stitching and Target Recognition

This section contains a description of our contributions in SAR image stitching and SAR ATR tasks.

A. Frame-based SAR Processing

Typically, SAR image formation onboard in real-time conditions is accomplished frame-by-frame. In terms of raw data processing, images are formed consequently from the azimuth blocks. The range dimension is determined by the swath width. Application of frame-based image formation algorithms gives a significant performance improvement due to utilization of fast Fourier transform (FFT) for range and azimuth focusing. The range-Doppler algorithm (RDA) is the most popular technique due to its functional simplicity [4].

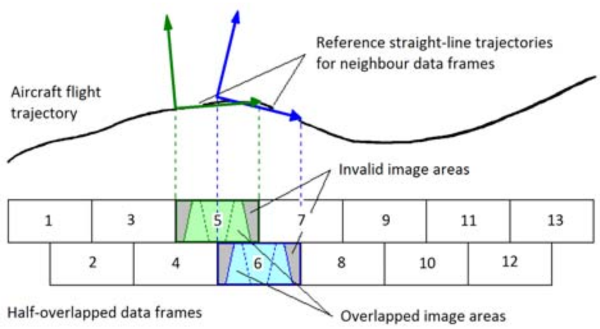

Fig. 4. Frame-based SAR processing.

Since the SAR platform is quite unstable, each SAR frame is built with its own reference trajectory (Fig. 4). Half-overlapping scheme is typically applied in order to account trajectory deviations while keeping the SAR panorama to be unbroken.

Due to peculiarities of image formation, obtained SAR frames have an unknown relative translation and rotation components. In particular, horizontal and vertical shifts $(\Delta x, \Delta y)$ and rotation angle φ. The common algorithm for stitching is to use the value of rotation angle calculated from the navigation system measurements [17]. After that, unknown shifts are estimated using two-dimensional cross-correlation.

In order to make the stitching more efficient, we propose to use computer vision inspired methods. Instead of using navigation data, speeded-up robust features (SURF) algorithm [18] is applied. Basically, it involves three key steps: keypoint detection, description and matching. The term keypoint or interest point corresponds to the pixels demonstrating the high local gradient. More details about principles of detection can be found in the original paper [18]. The descriptors are feature vectors constructed from local neighborhood around each keypoint. In the case of SURF, the feature vector is 64-dimensional [18]. The final step is descriptors matching. The output of this step is information about point-to-point correspondence in the pair of SAR frames. Ideally, it is enough to know this information about only 3 pixels. However, since accuracy is limited, it is better to use higher amount of matched keypoints. Fig. 5 illustrates an example of matched keypoints for a parts of adjacent SAR frames.

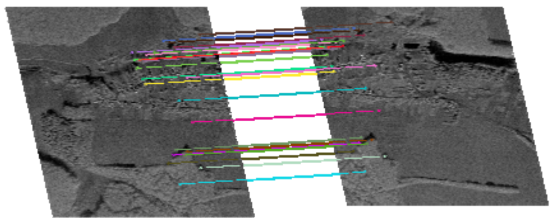

Fig. 5. Matched pairs of keypoints.

One should emphasize that keypoint matches should be properly filtered before estimation of the affine matrix between the analyzed SAR frames. Above described steps are accomplished consequently frame-by-frame in real-time basis.

B. Automatic Target Recognition

SAR ATR problem is another subject where pattern detection and recognition methods can be successfully applied. For this purpose, we have analyzed SAR images from moving and stationary target acquisition and recognition (MSTAR). Fig. 6 illustrates an example of samples from 10 classes.

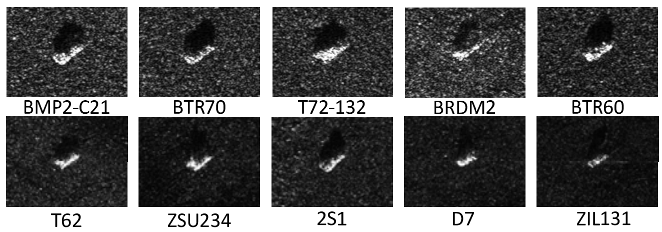

Fig. 6. SAR images of targets from MSTAR database.

MSTAR dataset represents a set of images of 1 foot by 1 foot (0.3m by 0.3m) resolution obtained in spotlight mode SAR operating at X band. The images were taken over 360 degrees covering different target orientations. One can observe that it is difficult to distinguish the target classes by the human visual system.

Initially, we have tested three groups of features. In particular, Haralick features [19], local binary patterns (LBP) [20] and proposed azimuth and range profiles of the target signature. Support vector machines (SVM) were chosen a tool of choice for classification.

Fig. 7 illustrates the initial classification results

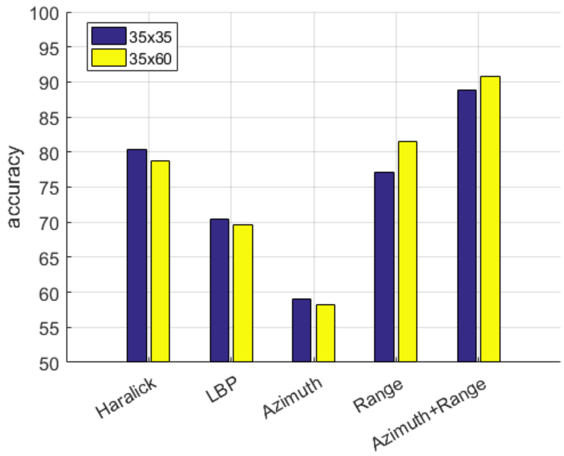

Fig. 7. SAR target classification results.

One can see that the fusion of azimuth and range profiles gives higher recognition accuracy. Initially, two sizes of regions of interest (ROI) were analyzed. Rectangular ROI size 35*60 gives the best results with accuracy equal to 90.7%. Interesting, that the size of feature vector is only 95 samples in this case. In contrast, Haralick feature vector is 195-dimensional, while LBP image feature vector is equal to the total amount of pixels in the analyzed ROI. In the near future, we will additionally study the potential of target profiles together with other feature groups.

IV. Conclusion

In the paper, several interesting applications of pattern detection and recognition algorithms in SAR images analysis were proposed. In particular, optical flow technique was integrated for automatic estimation of moving target parameters. Proposed preprocessing scheme allowed to increase the efficiency of such estimation. Secondly, developed image stitching solution can be used for SAR panorama creation without accouting of platform orientation. Finally, initial results of SAR ATR were shown. Usage of compact low-dimensional feature vectors has a good potential for real-time object recognition onboard.

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