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A METHOD OF TARGET TRACKING USING INVERSE SYNTHETIC APERTURE RADAR HIGH FREQUENCY ANALYSIS TECHNIQUE

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***Abstract*—** Image denoising is an important image processing task both as a process itself and as a component in other processes. The process of tracking the objects in space is gaining popularity with the advance of technology. Non-harmonic analysis is a high resolution frequency analysis technique that improves noise removal accuracy in which a multiframe marked point process model for automatic target structure extraction by tracking in inverse synthetic aperture radar image sequences and the process of tracking the images throughout its movement has been determined. To deal with scatterer scintillations and high speckle noise in the ISAR frames the resulting target sequence by an iterative optimization process, the observed image data and various prior geometric interaction constraints between target appearances in the consecutive frames is considered. Non uniform regions that occur due to segmentation are analyzed by an extended NHA method called Mask NHA. Finally quantitative evaluation is performed on image sequences of different carrier ships and airplane targets with the elimination of the scatterers present in the images thus reaching its specified destination region successfully.

***Keywords*—**Non-harmonic analysis; Multiframe marked point process; scatterers.

I. INTRODUCTION

The detection of the scatterers in the image and the elimination of it seem to be a tedious task nowadays .The method for classifying a ship based on a 3D model extracted from an ISAR image sequence has been dealt in the existing model of the target recognition. Traditionally, Inverse Synthetic Aperture Radar (ISAR) image frames are classified individually in an automatic target recognition system. When information from different image frames is combined, it is usually in the context of time averaging overlapping of the images takes place and remains a tedious task to remove statistically independent noise fluctuations between images. The sea state induced variability of the ship target projections between frames, however, also provides additional information about the target that can be used to construct a 3D representation of the target scatterer positions. This model gives the maximum of two to three frames. Numerous denoising methods have been developed in diverse fields of research. Katkovnik et al. in their review suggested a classification of denoising algorithms according to two features: local/non-local and pointwise/multipoint algorithms[6]. Priyam Chatterjee and Peyman Milanfar proposed a patch-based, locally adaptive denoising method based on clustering the given noisy image into regions of similar form of geometric structure. In order to effectively perform such clustering, features of the local weight functions is used. These weights are exceedingly informative and robust in conveying reliable local structural information about the image even in the presence of significant amounts of noise. Next, each region or cluster is built which may not be spatially contiguous by learning a best basis describing the patches within that cluster using principal components analysis[15]. Christo Ananth et al. [5] proposed a system in which an automatic anatomy segmentation method is proposed which effectively combines the Active Appearance Model, Live Wire and Graph Cut (ALG) ideas to exploit their complementary strengths. It consists of three main parts: model building, initialization, and delineation. For the initialization (recognition) part, a pseudo strategy is employed and the organs are segmented slice by slice via the OAAM (Oriented Active Appearance method). The purpose of initialization is to provide rough object localization and shape constraints for a latter GC method, which will produce refined delineation. It is better to have a fast and robust method than a slow and more accurate technique for initialization. Christo Ananth et al. [9] proposed a system which uses intermediate features of maximum overlap wavelet transform (IMOWT) as a pre-processing step. The coefficients derived from IMOWT are subjected to 2D histogram Grouping. This method is simple, fast and unsupervised. 2D histograms are used to obtain Grouping of color image. This Grouping output gives three segmentation maps which are fused together to get the final segmented output. This method produces good segmentation results when compared to the direct application of 2D Histogram Grouping. IMOWT is the efficient transform in which a set of wavelet features of the same size of various levels of resolutions and different local window sizes for different levels are used. IMOWT is efficient because of its time effectiveness, flexibility and translation invariance which are useful for good segmentation results.This simple detector using operators of several widths to cope with different

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signal-to-noise ratios in the image is taken for processing. Femto second laser pulses were used to excite second harmonic waves from collagen harvested from rat tail tendon and a reference nonlinear crystal. Second harmonic interference fringe signals were detected and used for image construction. Because of the strong dependence of second harmonic generation on molecular and tissue structures. as a frequency analysis method, non-harmonic analysis (NHA), which has high accuracy for detached frequency components is used and is only slightly affected by the frame length[3]. The spectrum subtraction method is one of the most common methods by which to remove noise from a spectrum. Inverse Synthetic Aperture Radar (ISAR) image shows the two dimensional reflectivity of a target by synthesizing the signal reflected from a target .Its range resolution is decided by the bandwidth. The cross-range is obtained by the Doppler frequency caused by the relative rotational motion between the target and the radar. Though the method seems to be simple the noise that are present in the images is not completely extracted that lead to the loss of data. Investigation into the 3D model extraction method is still in its preliminary stages, and the evidence for the usefulness of the technique is still only suggestive, and not conclusive. The proposed method brings vast advantageous over the existing system as it implies the use of the multi target analysis and elimination of the noise by means of the point process model has been delivered. Specifically, the result shown only shows that the estimated 3D models are, in some sense, consistent between image sequences, but there is no proof that this is because it reliably extracts 3D position information. This could be partially confirmed by checking whether a similar rate of comparison could be achieved by using the original 3D scatterer models as the template models. It is also not certain that it is only the 3D information that is producing the ship discrimination. This could be confirmed by comparing the 3D performance against that of a classifier based on the range profiles of the ship, or based on time-averaged feature based classifiers.

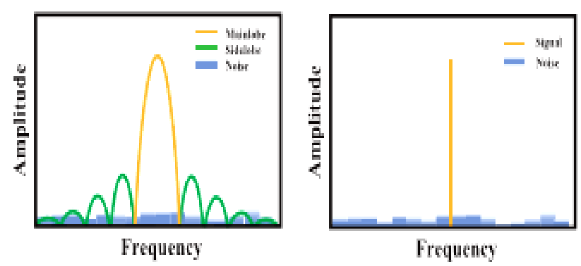

Fig. 1. The difference in frequency expression in a noisy environment between (a) traditional frequency analysis, and (b) high-frequency resolution analysis.

II.Proposed Method

Image formation

The ISAR images is segmented into foreground and background classes by a binary Markov random field model to decrease the spurious effects of speckle noise. The goal is to obtain a binary label map labels correspond to the foreground and background classes respectively. To get an initial estimation of the target axis segment,

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detect the axis line using the Hough transform of the foreground mask. This model enables to characterize whole target sequences instead of individual objects through exploiting information from entity interactions. Following the classical Markovian approach, each target sample may only affect objects in its neighboring frames directly. This property limits the number of interactions in the population and results in a compact description of the global sequence, which can be analyzed efficiently. Interaction potentials are responsible for involving temporal information and prior geometric knowledge in the model. Image denoising using domain transformation often employs a block unit called a "patch." The smoothing effectiveness of denoising increases with the patch size. The non masked analysis is a high resolution frequency analysis technique that removes the noise removal accuracy. The mask can be with horizontal and the vertical alignment of the pixel. The sum of products of the individual pixels are alligned using the neighbouring pixels. The mask is placed over individual pixels and the masking operation is performed. The edges of the image is determined accurately. The boundary can be detected without any of the blurring effect as the lower pixel values are removed over the high frequency resolution. The edges are detected clearly and also accurately without any loss of the data. Iterative refinement algorithm, which scans in each step the whole sequence and attempts to replace the actual objects with more efficient ones considering the data and prior constraints in parallel.

Masked Non Harmonic Analysis

The frequency resolution of DFT is limited by the integer period. If the period of the signal in the analysis window has a non-integer value, sidelobes are observed in the results. In an analysis of DFT, the frequency resolution is chosen according to the change in analysis window size. However, NHA estimates the Fourier coefficients by using sinusoidal in frequency analysis using DCT. In general, the frequency resolution depends on the window size.

The clustering performance taking into consideration depends on effect of the noise. The original signal can be distorted by the removal of the sidelobe through thresholding. This is the obstacle to denoising. NHA can suppress sidelobes using high-frequency resolution. Image denoising using domain transformation often employs a block unit called a "patch." The smoothing effectiveness of denoising increases with the patch size. However, the likelihood of the edge mixing with the patches increases when using large patches. The edge is transformed into the sinc function by DFT. When part of the error signal in the frequency domain is removed by thresholding, the restored image includes a ringing artifact. The performance of denoising method using natural images provoides the analysis of images using DFT and DCT leads to sidelobes. If the analysis

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window contains regions of different textures adjacent to each other, the corresponding signal in the analysis window is non-stationary. Hence, the input signal in the analysis window needs to be masked. The masking area is obtained from image segmentation results. In segmentation, the noisy image is classified into two regions, the edge region and the texture region. Moreover, texture region is classified into multiple regions using spatial similarity.

Target Axis Extraction Of Patch Based Images

To minimize the influence of signal non-stationarity, it is necessary to exclude edges and different textures from the analysis window. Most of the ATC/ATR systems that are based on radar images make use of a two-step approach to solve the problem: features are extracted from the radar image and then they are fed to a classifier that decides based on comparing such features with those that were previously stored in a database.

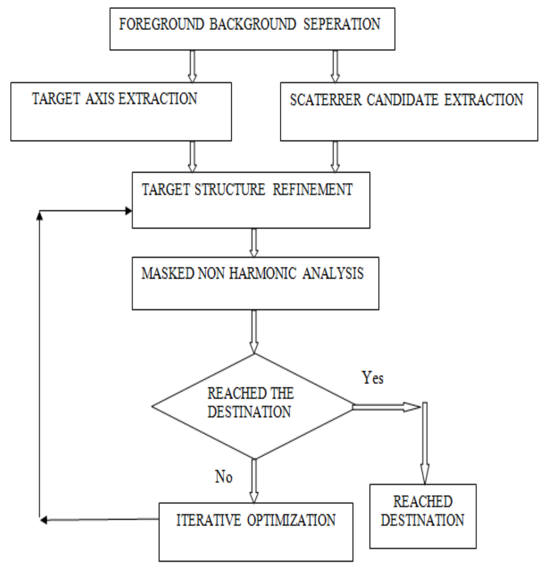

Fig 2 Workflow of proposed method

As scatterers may appear and disappear in ISAR images on the basis of shadowing effects or weak scattering mechanisms, the estimation of the target's size may be incorrectly performed. By observing a target for a longer period of time, scatterers typically appear and disappear from image frame to frame. Therefore, by using the ISAR image sequences, such shortcomings may be overcome. Sequences of ISAR images were used previously to improve both ISAR image formation and target's classification and recognition.

III. Problem Definitions And Notations

The input of the proposed algorithm is an n-frame long sequence of 2-D ISAR data, imaged in the range-Doppler domain, which contains a single ship (or airplane) target.

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Let it is denoted by S the joint pixel lattice of the images and by s ∈ S a single pixel. The amplitude of pixel s in frame t ∈ {1, 2 .. …. n} is marked with ξ. As the observed values may vary in a wide amplitude range for a more compact data representation of the images the input maps by taking the logarithm of the observed amplitudes, thereafter we apply linear scaling for normalization. The zero amplitude values are replaced with a small positive constant to avoid the calculation of log 0. The images corresponding to the sample frames in the normalized log-amplitude domain are displayed in gray scale. Apart from visualization, the logarithmic image representation suits well the widely adopted log-normal statistical models of the ISAR target segmentation. This paper is to measure relevant features of the objects, such as length or orientation, which provide us information for target identification and behavior analysis. The investigated ISAR images provide only very limited information about the superstructures of the targets, identify stable bright points in the images, called permanent scatterers, which can be tracked over the frames of the sequence .These characteristic features are produced by stronger scatterer from the illuminated objects.

IV DATA PREPROCESSING IN A DIRECT APPROACH

Data preprocessing is needed to prepare the data for subsequent analysis. It should be pointed out that some of the following methods rely on the fact that the image acquisition and therefore the system parameters are suitably tailored to handle certain type of targets. As an example, the range and Doppler extension of the imaged area should be larger than the range and Doppler occupation of the target. As the latter depends on the radar-target dynamics, this condition is not necessarily verified. Nevertheless, certain types of target and radar platforms typically produce predictable or at least bounded dynamics that can give direct information about the radar parameter settings that ensure that such a condition is 0 30 60 90 120 150 180 210 240 pixel intensity: normalized log–amplitudes empirical likelihood foreground background. Histogram of intensity values over a 18-frame long subsequence. Foreground and background regions are manually distinguished satisfied. This fact allows us to define foreground–background segmentation in a straightforward way.

Foreground–Background Segmentation

In the first step, the ISAR images is segmented into foreground and background classes by a binary Markov random field model to decrease the spurious effects of speckle noise. The goal is to obtain a binary label map labels correspond to the foreground and background classes, respectively. Assuming that the ξ-amplitude values in both classes follow log-normal distributions that model the log-amplitude posterior probabilities by Gaussian densities.

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To experimentally validate this model, foreground masks onto sample images is done and investigated the log-amplitude feature statistics in the foreground and background regions, respectively. This shows the histograms of the two classes, as a result of evaluating 18 frames selected from a 245-frame-long ISAR sequence with uniform time intervals, and observed that the Gaussian approximation is valid. To estimate the Gaussian distribution parameters of the foreground and background classes, one can choose either a supervised or an unsupervised approach.

Supervised models need manual foreground–background evaluation of a few sample frames; however, these key frames have to be carefully chosen as the range of amplitudes may slightly fluctuate over the sequences. A convenient way from the point of view of the system operator; however, as shown the log-intensity domains of the two classes are usually significantly overlapping, thus involving prior knowledge in the process may be necessary. The assumption of a prior estimation about the ratio of foreground areas compared with the image size, which was a reasonable assumption regarding large vessels, because the targets showed line segment structure and the imaging step intended to provide us spatially normalized images where the target is centered and the image is cropped so that it estimates a narrow bounding box of the target. Thereafter, a preliminary foreground mask was derived by thresholding the input frame followed by a pair of morphological closing and opening iterations, where the threshold corresponds to the value of the integral histogram. The preliminary mask too coarse for object shape investigations; however, it proved to be appropriate for estimation of posterior probabilities, as the estimated Gaussian parameters differed only slightly from the supervised estimation results. If pixel is in the four-neighborhood of pixel are in the S lattice then optimal foreground mask is derived through minimizing the following MRF energy function.

Initial Alignment and Line Segment Estimation

To get an initial estimation of the target axis segment, detect the axis line using the Hough transform of the foreground mask. At this point, there originates from the ISAR image synthesis module. The image formation process considers the images to be spatially periodic both in the horizontal and vertical, then, the imaging step estimates the target center, and attempts to crop the appropriate rectangle of interest (ROI) from this periodic image .However, if the center of the ROI is erroneously identified, the target line segment may break into two (or four) pieces. Therefore, in the proposed image processing approach, the longest foreground segment of the axis line in a duplicated mosaic image, which steps also, re-estimates the center of the input frame.

Scatterer Set Extraction

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Scattering mechanisms within the same resolution cell and to defocusing effects, the amplitudes may significantly vary over the consecutive frames, moreover we must expect notable differences between different scatterers of the same frame. Permanent scatterers cause dominantly high amplitude. Demonstration of the foreground–background segmentation has been represented. with background and foreground probability maps (high probabilities indicated with greater intensities). The foreground mask through pixel-by-pixel maximum likelihood (ML) classification based MRF optimization. The foreground mask by the proposed MRF model which effect is clearly demonstrated. Thus, determination of efficient global thresholds to extract all scatterers by simple magnitude comparison. Therefore focusing first on a high recall rate, a large group of scatterer candidates is extracted, which may contain several false positives. Thereafter, an iterative solution to discriminate the real scatterers from the false candidates, with utilizing the temporal persistence of the scatterer positions and the line structure of the imaged targets. A foreground constraint: search for scatterers in the ISAR image regions labeled as by the initial input binarization step. As the results in the real scatterers are efficiently detected in this way, but the false alarm rate is high.

Scatterer Filtering

The scatterer selection algorithm iterates various local moves, called kernels, in the object configuration space. In the following part of this section, two kernels are introduced and demonstrated their effects. Thereafter, the details of the complete spatiotemporal model and the iterative optimization process are given. The input of the scatterer filtering kernel is the actual estimation of the axis line segment and the PSC set. The kernel exploits two facts observed in cases of large carrier ships:

1) For a given target candidate, the scatterer candidates are choosen close to the axis line.
2) The projection of two different scatterers to the axis line should not be too close to each other, as the later artifacts are mainly caused by multiple echoes from the same scatterer. The minimal distance of two real scatterer projections in the domain is determined by a threshold parameter, which varied between 0.05 and 0.07.

Based on the above assumptions, a filtered scatterer set by a sequential algorithm is selected. However, this filter is by nature very sensitive to the accuracy of the preceding axis estimation step. As shown here applying the SF kernel directly for the output of the Hough based axis detector results in notably weak classification. For the above reason, a second move, which can be applied for scenarios where a strong line-arrangement constraint is valid for the real scatterer configuration. The RANSAC algorithm after

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obtaining a re-estimated axis, that the RANSAC kernel has a couple of limitations: it cannot be adopted, if there are only a few permanent scatterers on the target's image and the RANSAC-estimation may fail in cases of multiple duplicated scatterers in the PSC set that can form parallel lines. The later artifact can appear as a consequence of echoes in the imaging step. However, assuming that the target structure is fixed, and the position and orientation displacement is small between consecutive frames, temporal constraints can be exploited to refine the detector.

Edge Preservation Of target Images

The Canny edge detection [22], which is commonly used to identify edge position. It uses a smoothing process prior to edge detection. The smoothing method often uses a Gaussian filter, but this distorts the edge position if it is used in Canny edge detection. An edge-preserving smoothing method is thus needed. Patches that lie near the boundaries of a cluster or those that may have been misclassified. Hence, instead of combining the different estimates of the same pixel, it simply retains the intensity estimate for which the pixel is at the center of the patch being restored. The accuracy of Canny edge detection by using bilateral filtering is determined [23],[24]. A bilateral filtering is an edge-preserving filter that uses weights defined according to the difference of pixel luminance between the pixel of interest and its neighboring pixels.

As the observed object's structure can be considered rigid, a strong correlation between the target parameters in the consecutive frames received. Because of the imaging technique, the center is not relevant regarding the real target position, thus only penalize high differences between the angle and length parameters and significant differences in the relative scatterer positions and scatterer numbers between close-in-time images of the sequence. The prior interaction term is constructed as the weighted sum of four sub terms the median angle difference ,the median scatterer number difference and the median scatterer alignment difference .

V. Optimization

An image needs to be divided into clusters without edges in order to prevent ringing artifacts. However, the boundary definition of each region with uniform texture is difficult to provide using existing segmentation methods. Thus, it is difficult to determine the boundary of a region within a noisy image. Optimizing is usually performed with iterative stochastic algorithms, such as the reversible jump Markov chain Monte Carlo sampler or the multiple birth and death dynamics. However, in contrast to the above MPP models, in the proposed system, a single object is tracked across several frames in the input sequence, where the geometrical constraints are strong between the expected object parameters in near ISAR images. For example, the length and orientation of the

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imaged target cannot change significantly within a short observation period. As a consequence, the weight of the prior geometric terms increase and the iterative optimization process becomes sensitive to be stuck in local. Solution is initialized with the output of the preliminary detector of which provides an initial configuration which is in most of the frames reasonably consistent with the input data. Thereafter, we proceed to an iterative refinement algorithm, which scans in each step the whole sequence and attempts to replace the actual objects with more efficient ones considering the data and prior constraints in parallel. The two key points of this procedure are

1) the generation step of new object candidates

2) the evaluation step of the proposed objects

with regard to the current configuration and the input data. For object generation, we use two types of moves: the perturbation Kernel and the RANSAC-based birth kernel, which are chosen randomly at each step of each iteration. The perturbation kernel clones the actual object either from the current or the previous or the next frame; and it adds zero mean Gaussian random values to the center. Finally, the scatterer positions are cloned from the object of the current frame and optionally additional scatterers are added or some scatterers are removed.

VI CONCLUSION

In this method detection and tracking of the aircrafts and ships which are the moving target in ISAR image sequences using energy optimization process. By this the axis, the points and the moving target are extracted detected and tracked respectively. In the presence of noise sequences a multi frame marked point process model is introduced to remove the noise. Hence the resulting target sequence is obtained by iterative optimization process by simultaneously considering the observed image data and various geometric constraints. outperformed the other methods with regard to sidelobe comparison but was inferior to them with respect to modular index values. In addition, a comparison of the image showed that pixel differences yield a similar result to the threshold value.

This indicates that denoising can be facilitated by image segmentation and edge preservation. The main limitation of this work is that the performance of the proposed method is dependent on the parameters in the partial processes. In future research, it is planned to replace edge-preserving segmentation with a superior method. For instance, the edge regions and homogeneous regions should be defined using frequency domain parameters. Further, a method to determine the threshold values is also to be considered.

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