Radar target detection based on methods of image pattern matching

Ling Tong, Frank Heymann, Thoralf Noack

German Aerospace Center (DLR)
17235, Neustrelitz, Kalkhorstweg 53, Germany

Abstract

This paper studies the performance of pattern matching algorithms with the goal of the detection and tracking of vessel targets in maritime radar images. We compare different methods using a database which consists of radar images from two different manufactures. The data covers a timespan of roughly 4 hours with a one second time resolution. The performance of 3 template matching and 5 feature detector algorithms is tested and the most suitable algorithm is chosen for further optimizations. These optimizations are based on the properties of the radar images and the properties of the radar target.

1. Introduction

Radar, an acronym for "radio detection and ranging", which uses radio waves to discover objects and to determine their spatial locations, is an essential tool for maritime surveillance. ARPA (Automatic Radar Plotting Aid) is an added tracking feature on the basis of the traditional radar. It can provide attitude data and collision avoidance information automatically and continuously by calculating the course and speed of the objects to be tracked. However, due to their functional limitations [1], the existing ARPA products are still not able to be used for a reliable tracking. Therefore, accurate and fast detection of radar targets is still one of the principal unresolved technical issues.

In this paper we focus on the target detection in radar images using the technique of 2D image processing and methods of computer vision. The paper is structured as follows; Section 2 describes the utilized database and the strategy of our study. Section 3 gives an introduction to a sample collection of image matching algorithms used in this study. In section 4 we present and discuss our results. Some improvements for an effective and efficient application of the approaches in radar target tracking are presented in section 5. In section 6 we finally conclude our findings.

2. Database and strategy

The data used in this paper consists of radar images from the radar training location of the "Schifffahrts Institut Warnemünde" in Rostock. The radar screen was stored every second as an image file using a VGA2USB [2] converter. During our 4 hour measurement campaign we were able to collect the data from two different manufactures, namely Sperry Marine [3] and SAM [4]. The final database consists of 18.6 gigabyte (Sperry 11.9 GB, SAM 6.7GB) stored in 16339 PNG image files (Sperry 9494, SAM 6845).
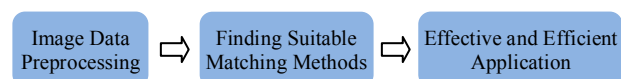

Fig. 1. Strategy of our study

The strategy of our study is illustrated in figure 1 and consists of three steps.

After storing and sorting the data files, we optimize the images according to the properties of the maritime radar. For example, as shown in figure 2, we are only interested in the circle in which the radar reflections are visualized and not in the additional graphical user interface. In addition, we extract a sample collection of targets (subpatterns) which are selected by eye. As shown in figure 3 the
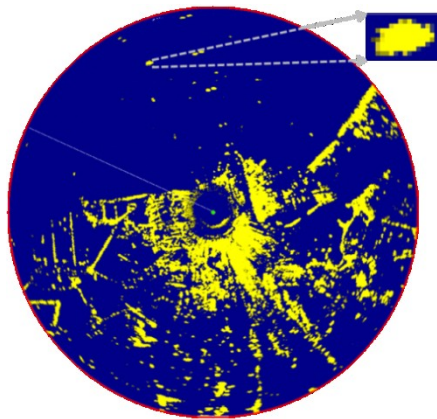
Fig. 2. This figure shows the subpattern extraction. The large blue circle is the radar screen and the smaller rectangle describes a zoomed version of the extracted pattern patch
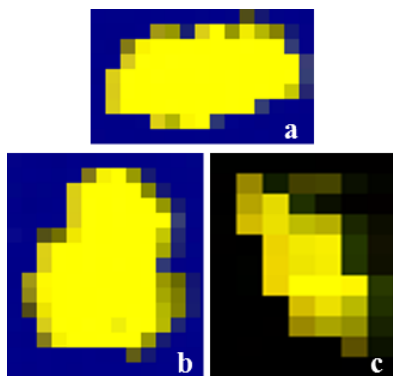

Fig. 3. This figure shows three zoomed versions of our subpattern collection. The subpattern a and b are from the SAM radar while the c subpattern is from Sperry Marine. These patches show similaritys with an elliptical shape

subpattern consists of the target itself and an one pixel border, which is defined by a threshold operation using the median value between 0 (black) and 255 (white), namely 127, as threshold value.

In the next step we attempt to identify the most suitable pattern matching algorithm, which is provided by the open source image processing library OpenCV [5]. We start the search with the test in which each method has to find the subpattern (Fig. 2) in the original image it was extracted from. We consider only methods for further investigation which pass this initial test. The additional test is described in more detail in section 4.

In the final step we chose the most suitable extraction algorithm to test it on real life data.
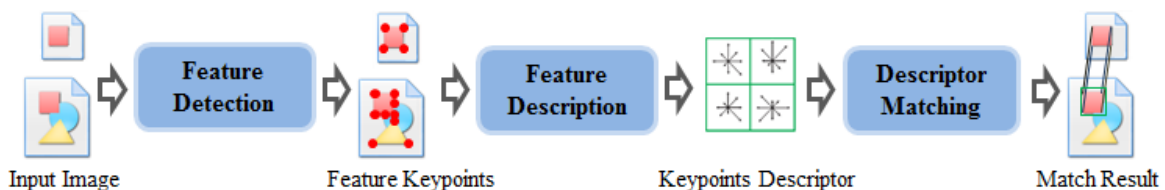
The method and all optimizations are described in section 5.

3. Image matching approaches

Image Pattern matching algorithms can be broadly classified into two major categories of approaches: Feature Based Matching (FBM) and Area Based Matching (ABM) [6], as shown in table 1.

Table 1. Feature Based Matching and Area Based Matching

Image Matching Algorithms	Matching Entities	Matching Strategy
Feature Based Matching	Features: Curves, Edges, Regions	Feature Extraction, Feature Description and Descriptor Matching
Area Based Matching	Gray levels	Similarity Measure or Distance Measure

Feature-based matching approaches extract image features, such as special points, curves, edges, regions, etc., and attempt to establish the correspondence between the features of the pattern patch and the input image. Its matching strategy is based on the image processing of feature extraction, feature description and descriptor matching.

Area-based matching which is also known as *Template Based Matching* (TBM) matches a sample template patch against an input image by "sliding" the patch over the image. Its matching algorithm is based on a distance or a similarity measure of the intensity values of template patch and input image.

3.1. Feature Based Matching (FBM) approaches

Feature based matching has found widespread application in many areas of computer vision, such as face recognition, 3D stereo Reconstruction, and images registration.

In the FBM, only the selected points with certain features, such as end points, curves, corners, edges, regions, etc., are to be matched. As illustrated in figure 4, in the first stage of matching process, the image pair is preprocessed by using a so-called feature detector that attempts to extract specific feature key points. In the second stage, the feature vectors, namely the descriptors are calculated to describe the visual information of a feature point's

Fig. 4. Schematic process flow of the feature based image matching approaches

neighborhood [5] which can be used to characterize the feature point and make it distinguishable from the others. To learn more about feature description please read the reference book [7]. The corresponding feature pairs between the pattern patch and the input image would be found in the last stage.

In view of the issue that the targets to be matched in the radar image only have few pixels (about 100 pixels), as shown in figure 3, and information carried by pattern patches are consequently few, the most important stage in our case is the detection of the key points with significant feature, and thus we chose a standard feature descriptor and a standard feature matcher, and test the feature detectors listed below:

- SIFT: SIFT [8], stands for Scale Invariant Feature Transform. The detector is resistant to the most common image transformation, such as scale, rotation and lighting.
- SURF: The Speed-Up Robust Feature detector (SURF) published by Bay [9] in 2006 overcomes the computational cost of SIFT without affecting the quality of the detected points.
- Harris: Harris Feature Detector was presented by Harris [10] in 1988 for the detection of corner feature-points.
- FAST: The FAST Feature Detector [11] modified the Harris corner detector in order to speed up the algorithm without compromising the results.
- Dense: Using Dense Feature Detector, the features points are distributed densely and regularly over the image.

3.2. Template Based Matching (TBM) approaches

Template based matching is a technique of computer vision widely used in finding areas of an input image that are similar to a template image patch by pixel-wise "sliding" the patch over the input image, using one of the matching methods described in this section.

The way to achieve template based matching is by using a similarity or distance measure between a template image and an exactly matching region in the image. It is necessary to find the maximum similarity or minimum distance [12]. The result similarity $S(x, y)$ can be computed from the image data I and the template patch T as:

$$S(x,y) = \sum_{x_T=0}^{w-1} \sum_{y_T=0}^{h-1} \left| T(x_T, y_T) - I(x + x_T, y + y_T) \right| \quad (1)$$

x, y are the coordinates of the image, and x_T, y_T define the location in the template patch with a width w and a height h. The summation will be done over the template patch.

- Cross Correlation (CC): The CC multiplicatively matches the template patch against the input image, and in each position the cross correlation between the template patch and the corresponding part of the input image is computed.
- Correlation Coefficient (CCOEFF): The CCOEFF matches a template patch relative to its mean against the corresponding part of the input image relative to its mean.
- Sum of Squared Differences (SSD): The SSD minimizes the squared difference between a template patch and the corresponding region of the input image.

4. Results – Comparative study

To identify the suitable matching approaches listed in the last section, two kinds of tests are executed, i.e. the initial test and the real time (RT) performance test. To pass an initial test, each method has to find the subpattern, as shown in figure 2, in the original image it was extracted from. We consider only methods which pass this initial test for further investigation. In the RT performance test, we test the approaches which already pass the initial test if they meet our real time requirement, namely each image should be processed less than one second. This section aims to list our test results, and that begins with an explanation of the outcome of the testing of the different matching approaches.

- SIFT/SURF: These two methods are also called texture based detectors [13]. They cannot detect enough feature points for matching if the target has only few pixels just like the targets in our pattern patches in figure 3. SIFT and SURF feature detectors didn't pass our initial test.
- Harris/FAST: The issue that the Harris and FAST detectors detect corners prioritized over edges [13] while the features in our patch, as shown in figure 3, are dominated by edge, makes the two detectors not reliable in the initial test.
- Dense: The dense method passes the initial test but the computing time of matching is so long, namely about 5 or 6 seconds (tested on a PC with 2 processors clocked with 3 GHz and 4 GB memory) that cannot meet our requirements of real-time tracking (one image per second). Therefore, the dense feature detector cannot be taken into account.
- CC: The method CC fails our initial test. Due to the issue that the best match will be the coordination point with the maximum result of the cross-correlation, this method fails when there is an object in the image brighter, namely with

Table 2. An instance of when the cross correlation is unable to provide the correct match

a	b		m	m
c	d	$*$	m	m
Template patch			Image patch with constant grey value	
$(a, b, c, d > 0$ and $m > 0)$				
Result: $m \cdot (a + b + c + d)$				

a	b		n	n
c	d	$*$	n	n
Template patch			Image patch with constant grey value	
$(a, b, c, d > 0$ and $n > m > 0)$				
Result: $n \cdot (a + b + c + d) > m \cdot (a + b + c + d)$				

larger grey value, than the target. Table 2 shows schematically an instance of when the cross correlation is unable to provide the correct match, i.e., the cross correlation of the template patch and an Image patch with constant grey value m (the first cross correlation) is less than the cross correlation of the template patch with a brighter patch with constant grey value n (the second cross correlation), under the premise that both template patch and image patch are not a black patch (a, b, c, d, n and $m > 0$). In this case, the second cross correlation always has larger score, regardless of what the template is! To avoid this flaw of the method CC, we can subtract the mean value of the template and calculate the co-efficient of the cross correlation, namely, correlation coefficient.

– CCOEFF: This method passes the initial test. Using this method, we get a higher score of similarity only when the darker parts of the template patch overlap darker parts of the input image, and brighter parts of the template patch overlap brighter parts of the input image. This method meets also the RT requirement.

– SSD: The SSD passes our two tests, and it is faster than CCOEFF.

To compare the matching approaches, we list the advantages and drawbacks of the tested approaches for the application in the field of radar target detection in table 3, according to their working principles and their application conditions.

The feature based matching approaches use only some distinctive features instead of the entirety of the image, therefore, the data processing can be more computationally efficient. On the other hand, FBM normally requires sophisticated image processing for feature extraction and a reliable matching depends consequently on the robustness of feature detection. In view of these facts, featured based approaches are typically applied when the pattern patch has "strong" features, i.e. the local structural information is more significant than the information carried by the intensity levels of the image, such as the applications in face recognition and panorama generation. Obviously, our pattern patches are not that case. Accordingly, the FBM approaches may only be applied as a supplement in special cases of radar target detection.

The template based matching approaches are best suited for detecting objects which do not have sufficient strong features, or for the matches that are estimated directly based on the bulk of intensity values. Moreover, although the TBM requires a vast data processing, the computing time is short enough for a real time tracking.

According to the comparative study of the above algorithms, we decide to utilize the template based matching approach *SSD* for the target detection.

Table 3. Comparison of image matching approaches

Approach		Advantages	Drawbacks	Suggestion
FBM	SIFT/ SURF	scale, rotation and lighting invariant	cannot find enough key points in case of lack of pixels	fails the initial test
	Harris/ FAST	scale, rotation lighting and noise invariant	detecting corners prioritized over edges	not reliable in the initial test
	Dense	dense feature points	too slow (about 5 or 6 seconds)	fails RT requirements
TBM	CC	the simplest measure	not invariant to lighting, scale and rotation	not reliable in the initial test
	CCOEFF	invariant to lighting	not invariant to scale and rotation	suitable
	SSD	invariant to lighting, fast	not invariant to scale and rotation	suitable

5. Efficient and effective application of TBM in radar target tracking

The analysis in the last section shows that the TBM also has its drawbacks, such as that the intensity distribution of the template and input image must be similar, in particular, the TBM is not invariant to rotation, and it often requires a vast data processing. In order to overcome these drawbacks and achieve a radar target tracking, the following measures have been taken for the effective and efficient application of the template based matching approaches.

5.1. Adaptive Template Update

In this paper we attempt to follow a target of interest through a series of radar images by finding the location in each image which best matches the pre-selected template patch containing the target.

The major drawback of applying the template based matching in the field of radar target detection is that the TBM is not invariant to rotation. In addition, the intensity distributions of targets sometimes vary greatly between images of long time intervals. That means the template patch that we used at the beginning of the match may not be suitable for the matches after a certain time. Therefore, we continually update the template, to reduce this drawback.

To minimize the erroneous matches caused by the target rotation, we extract the match result of the previous moment and save it as the template patch for the matching process at the next moment, this is the so-called winner update scheme, i.e., after each matching, the "winner" of the match will be saved as new template for the next match. It is necessaray to ensure the correctness of the winner, otherwise a wrong object will be tracked in the next moments.

In consideration of the size difference of the target between two adjacent images, the size of the new template should be adaptability changed. To implement this idea, at each moment, the new template patch which is obtained from the previous moment should be checked if there is still one pixel background border on all sides, as shown in figure 3 in section 2. In fact, this one pixel border plays the role as a buffer in order to compensate a size change of the target in the next image.

5.2. Setting a Region of Interest (ROI)

Another drawback of template based matching is that it required a "wasteful" pixel-wise scanning of the input image and computing a similarity or distance measure for each position of the whole image. The radar scan area is usually larger than the area that a ship can reach within the interval of adjacent radar images in a dataset.

Take for example, the SAM radar [4] images in our datasets. The scan area of this radar images is a circle with a radius of 3 nm (nautical miles). The interval of adjacent radar images is one second. The current world's water speed record as of 1978 is 511 km/h (i.e., about 0.077 nm/s) which was achieved by the boat Spirit of Australia [14]. In comparison with the 3 nm circle this 0.077 nm is only a tiny part of the entire image. Thus, it is really not necessary to scan the entire image. In response to this issue, setting a region of interest can reduce the computational cost on one hand, and it can also avoid unnecessary erroneous match on the other hand.
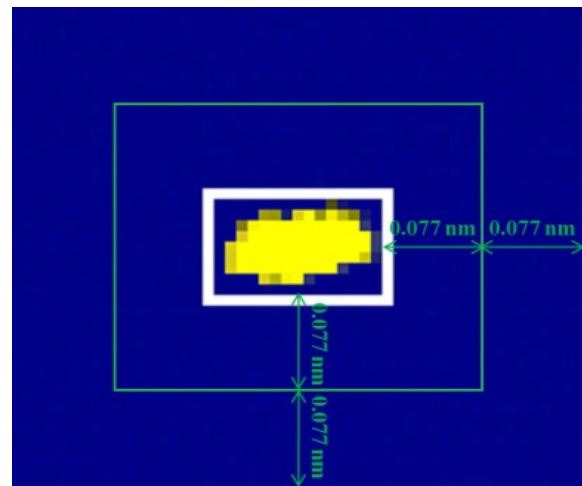
Fig. 5. This Figure illustrates what we define as Region of Interest (ROI)

As depicted in figure 5 that we extend a length of 0.077 nm on each side of the target forms thereby a rectangular area. The area inside of the green rectangle is the region with possibilities that the target may appear in the next second. The further extension of 0.077 nm on each side of green rectangle which can also be called as buffer zone is used to ensure that the target cannot come outside of the region by any possibility, such as, in the case that one image is missing, or the reflection area of the target in next radar image increases suddenly.

The conservative allocation of such a large buffer zone aims to cover all the unknown exceptions. Coupled with the buffer zone, we obtain the region of interest. The size of ROI in pixels in radar images can be calculated from the radial ratio of range setting, i.e. nm/pixel.

Now, the scanning and matching process only takes place within the region of interest. The relative position of the ROI in the input image responds to the position changes of the target. Consequently,

Fig. 6. Sample Tracking Results: a) Sperry Marine Radar [3], b) SAM Radar [4]

the location of ROI should be recalculated every time after the matching and saved for the extraction of the ROI in the next input image.

5.3. Tests with radar image datasets

Through the above two improvements, erroneous matches are reduced, computational resources are saved, and the performance is increased.

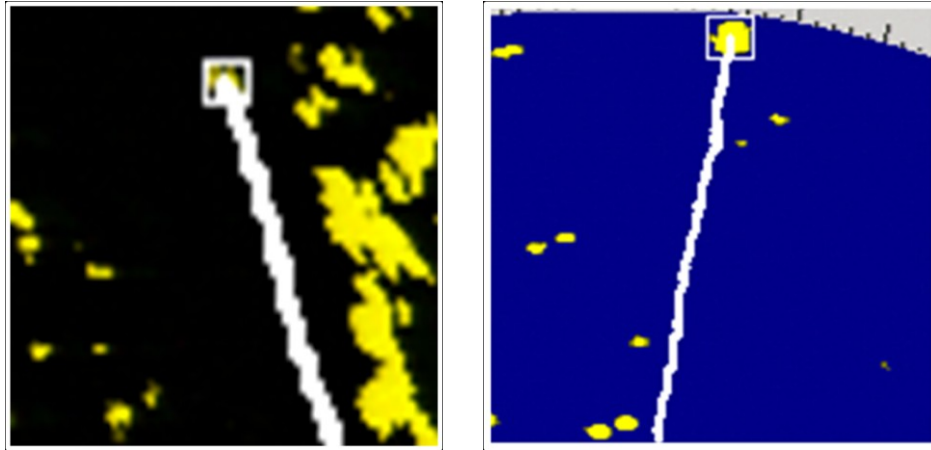In order to test the prototype of our radar target detector, the detector is instantiated with radar image datasets from two radars: *Sperry Marine* and *SAM*. Both radar devices were installed at Rostock coast. As shown in figure 6, the white curve shows the track of the target.

In figure 6a the detector has successfully tracked the target for 3.5 minutes (210 images), and in figure 6b the track was 7.5 minutes (500 images), without losses (100% tracking proofed by eye). The test results showed that a target can be detected and tracked when its intensity distribution does not vary greatly in adjacent radar images, i.e. the case of non-interference.

Conclusions

In this paper we tested 8 pattern matching approaches and we also discussed the possibilities of the applications of these approaches in the field of radar target detection. Finally, we identified the template based matching approach *SSD* is more suitable for detecting targets in radar images. In order to more effectively and efficiently apply this approach, and achieve radar target tracking, several improvements are implemented in a software prototype of radar target detector. To test our solution, the detector is instantiated with image datasets from two radars that were installed at Rostock coast. The test results showed that a target can be detected and tracked, when its intensity distribution does not vary greatly in adjacent radar images, i.e. the case

of non-interference. A comprehensive validation will be done in future work.

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