A Novel Approach for Ship Recognition using Shape and Texture

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***Abstract*:**

Maritime security includes reliable identification of ship entering and leaving a nation's territorial waters. Sea target detection from remote sensing imagery is very important, with a wide array of applications in areas such as fishery management, vessel traffic services, and naval warfare. Automated systems that could identify a ship could complement existing electronic signal identification methods. A new classification approach using shape and texture is introduced for Ship detection. Texture information can improve classification performance. This approach uses both shape and texture features. Feature extraction is done by Hu's moment invariants with several classification algorithms. This paper presents an overview of automatic ship recognition methods with a view towards embedded implementation on optical smart cameras. Therefore this approach may attain a good classification rate.

***Keywords*:**

shape and texture, Hu's moment invariants, ship recognition, smart cameras

1. Introduction

This section provides an overview of related work in ship recognition. Most of works cited involve SAR images. Ship recognition from remote sensing imagery is very important and has a wide array of applications such as fishery management, vessel traffic services, and naval warfare. In particular, in recent years, because of the decrease in fishery resources in the world, ship recognition has become much more important for effective and efficient ship monitoring to prohibit illegal fishing activities in time. Remote sensing plays a very important role in ship monitoring due to some of its virtues such as a long operating distance and a wide monitoring range. Maritime security includes reliable identification of ship entering and leaving a nation's territorial waters. Visual surveil-lance systems that could identify a ship complements existing electronic signal identification methods

Many papers have worked on ship detection based on SAR2 images [15]. SAR images methods expend largely and can only obtain target points, which cannot be used to recognize targets. There are also some papers that use remote sensing images for ship detection [16]. They present a method based on cumulative projection curve (CPC) to estimate the number of ships of small size, which is only efficient on especial images from stationary ships along coastline in a harbor. One of the few researches that uses color feature, from Lab color coordinate system, for sea target detection is [13]. They presented a definition on the degree of overlap between two clusters and developed an algorithm for calculating the overlap rate. Using this theory, they also developed a

DOI : 10.5121/ijait.2011.1503

new hierarchical cluster merging algorithm for image segmentation and applied it to the ship recognition in high resolution images is one of the several papers that worked on IR images. They used PCA, Bayes classification and wavelet-denoising to classify the sea targets, but in several papers, limitations and disadvantages of the methods based on statistical analysis are pointed out [17]. One of the papers that have more superiority to previous works in visible images domain is [18]. Their work is based on calculating different chaos by obtaining largest Lyapunov exponent of target and sea background which is not appropriate for images that contain seaside or some low chaos objects. Also the authors have proposed [17] based on the natural measure feature. Although the results of the method are considerable for some images but it still suffers from previously mentioned imperfection and needs analyzing several frames for exact results. So it is still important to find new methods of detecting target from sea background. Except [13] all above researches have worked on grey level images and for sure our method is one of the few one that utilizes color feature for sea target recognition.

A new method based on combinatorial improved PNN3 model for ship detection in SAR imagery and [23] proposes a method to reduce speckle noise for SAR images and to improve the detected ratio for SAR ship targets from the SAR imaging mechanism. A specific technique for automatic spot detection, based on the Wavelet Transform is presented and justified in [11]. Marivi et al [9] proposed a ship target detection method of SAR images by means of the discrete wavelet transform, taking advantage of the difference of statistical behavior of the vessels and the sea. Gouallier and Gagnon [4] reported work on SAR images. Sanderson et al. [20] proposed global feature extractors based on normalized central moment functions introduced by Hu [2] and PCA, and local feature extractors based on the 2D Hadamard transform. The classifiers used were based on Gaussian densities and Gaussian mixture models.

Feineigle et al. [14] reported work on optical imaging for harbour surveillance. Their approach is based on the scale invariant feature transform algorithm (SIFT) introduced by Lowe [8],[22]. Key point detection is used in computer vision to detect points of interest (i.e. features) in images which also can be assigned to objects. SIFT is a robust key point detector algorithm but it is computationally very expensive and most implementations run on PCs. During system operation, images are first extracted from the video camera. Next, the images are pre-processed or cleaned up to improve the results. Region-of-interest (ROI) identification will isolating a ship from its surrounding. Depending on the algorithm employed, such as the case with background subtraction or frame differencing, a reference frame may be needed [19]. After the ship is isolated and segmented, features which represent the shape are computed. Finally, the features are used to classify the object to a known type of ship or otherwise.

2. Extraction of Ship Candidates

2.1 Image Segmentation

In sea images, a stationary gray distribution [24] with a slow variation in the sea region usually exists, whereas usually, an obvious edge between the ship and sea due to a high ship hull is observed. Thus, image segmentation with edge information can be applied to extract possible candidate regions, which may include many false alarms such as islands, clouds, and ocean waves due to their similar edge characteristics with those of ships. On the other hand, there is usually a strong wake round steering ship, and it is sometimes difficult to distinguish the ship and the wake in optical images with low resolutions. When the ship and its wake are segmented into one region, the area is expanded, which often helps us find the small ships. Thus, they are considered a whole part in the following processing. In the experiments that involve extraction of ship candidates, only the original regions of more than ten pixels in size and more than four pixels in length are considered for analysis.

Image pre-processing: There is sometimes a dark gray distribution of ships, which has a negative effect on ship segmentation. However, there is usually obvious edge information around the ship. To enhance the distinction between the ship and sea to extract the whole ship, a new mixed image is proposed. The new mixed image is computed with the original gray value and edge magnitude as follows. Suppose that $f(i, j)$ is the gray value of a point (i, j) in an image. Then, the Sobel operator is applied to compute the edge magnitude $Mag(i, j)$. The mixed image is defined as

$$Mixf(i, j) = f(i, j) + a \times Mag(i, j) \qquad (1)$$

where a is a coefficient that controls the proportion of the edge magnitude to gray value, which was experientially set to equal to 1 in our experiments.

Coarse image segmentation: The whole ship region is relatively salient in the mixed image, ship candidates can be obtained by coarse image segmentation of the mixed image with a proper threshold. Here, a simple and effective segmentation method based on the optimal principle of maximum between-class variance and minimum within-class variance [3] is used to compute a global adaptive threshold. Furthermore, a region-filling algorithm [5] is adopted to delete the holes within regions, and morphological open and close operators with a three-pixel-diameter circle element [5] are adopted to eliminate very thin lines and random noise regions, which are perhaps generated by ocean waves for example.

Refined image segmentation: Due to the usage of only a global threshold, the coarse segmentation results may have edge localization errors. This processing aims at refining every region's contour with the local characteristics for the following feature extraction. A level set by the Chan–Vese model [5] is adopted to refine image segmentation. Chan and Vese (2001) proposed an algorithm based on the Mumford–Shah model, which can provide an optimal partition of two classes. The simple energy function is given as follows:

$$F(C) = Fo(C) + Fb(C) = \int_{inside(C)} |u(x, y) - co|2 \, dx \, dy + \int_{outside(C)} |u(x, y) - cb|2 \, dx \, dy \qquad (2)$$

where co is the mean value inside of the curve C, and cb is the mean value outside of the curve C. The minimum energy given by the Chan–Vese model will be an optimal piecewise smooth approximation of the edge. A level set is done on the corresponding subimages that are cut from the original images, with ranges depending on the ranges of segmented regions with adaptive thresholds. The initial curve C is set as the edge of the coarse segmentation

2.2 Simple Shape Analysis

After image segmentation, simple shape analyses can be applied to eliminate obvious false candidates. First, ships have a limited area, length, and width range. According to this constraint, false candidates such as very large or very small islands and clouds can be eliminated with proper thresholds, which should take the wake imaging into account.

Second, ships are commonly long and thin. Thus, the ratio of the length to the width of the region founding rectangle [6], [7] is larger than a given threshold. According to this condition, obvious false alarms, including islands and clouds with very small ratios, are eliminated. The relatively low threshold aims at keeping us from eliminating ships that may be either amid a curved wake or too small to exactly extract the ratio value. It aims at having a low missing alarm rate. Ship candidates are detected by image segmentation and simple shape analysis, as previously discussed. In our experiments, to reduce the time consumption, the level set is done after the simple shape analysis: only ship candidates need refined image segmentation with level set. It is easily concluded that the refined segmentation results with level sets are closer to the true ship edges than those with an adaptive threshold due to the use of local gray characteristics.

3. Extraction of Shape and Texture

It is important to extract effective features to distinguish ships from other objects, which mainly comprise clouds and ocean waves. Both shape and appearance attributes are crucial for each object class. In our approach, various features, including shape and texture, are extracted from a ship candidate and are concatenated as a feature vector for classification.

3.1 Shape Feature Extraction

Binary images, which are obtained from image segmentation, readily provide simple geometric properties such as perimeter and area. In our approach, the following shape descriptors are adopted.

Compactness: Compactness is given as [7] Compactness = $(\text{Perimeter})^2/\text{Area}$ The most compact region in a Euclidean space is a circle.

Convexness: Let S represent a set of contour points obtained from level set and $CH(S)$ [6], [7] be defined as its convex hull. The convexity measure is defined as

$$CM(S) = Area(S)/Area(CH(S))$$ [6], [7].

Rectangularity and Eccentricity: The simplest eccentricity [7] is the ratio of the major to the minor axes of an object approximated by its best fit ellipse. Ships are commonly long and thin; therefore, it can be adopted as a shape feature. Rectangularity [7] is the maximum ratio of region area to the area of a bounding rectangle according to its different directions. It assumes values in the interval (0, 1], with 1 representing a perfectly rectangular region.

Moment invariants: Moments are extensively used for shape representation, pattern recognition [7], and image reconstruction, which makes them a very useful feature set to include. Here, we adopt the first seven moment invariants[1] introduced by Hu [10].

3.2 Texture Feature Extraction

After taking a close look at these candidates that have been expanded to more than 100 pixels, we consider that most candidates are large enough so that some stable features can be computed from the gray distribution. Furthermore, little difference between the gray distribution of a ship and that of a nonship can be observed. Texture analysis can be applied to eliminate false alarms.

In this approach, besides commonly used features such as simple texture features, wavelet-based features, and multiscale Gaussian differential features (MGDFs), a new texture operator, LMP, is introduced to enhance the representation ability of the feature set. Simple texture features include mean, variance, moments, and entropy of gray value . Other features are described briefly as follows.

Wavelet-Based Features: Wavelet-based features aim at extracting the information in the frequency domain, and their capability of undergoing texture analysis has been shown [10]. By applying the wavelet transform to the candidate image, a number of subbands are generated. For each subband $I(l,s)$, the following features are calculated [10]:

$$e_1^{(l,q)} = 1/A \sum_j \sum_j \left| I_{i,j}^{(l,q)} \right|$$

$$e_2^{(l,q)} = -1/\log A \sum_j \sum_j \left(\left| I_{i,j}^{(l,q)} \right| / anorm \right) \log \left(\left| I_{i,j}^{(l,q)} \right| / anorm \right. \quad (3)$$

$$\text{Where } anorm = \sum_{i,j} \left| I_{i,j}^{(l,q)} \right|)$$

A is the area of each subband, l is the decomposition level, and q represents the subband number within the decomposition level l. The feature $e_1^{(l,q)}$ shows the amount of signal energy at a specific resolution, whereas $e_2^{(l,q)}$ shows the nonuniformity of the subband values.

4. Classification

The ship recognition pipeline in the smart camera consists of three stages. At stage 1, a ship image of 640×480 pixels is acquired and cleaned up for the following stages. This is necessary to remove noise as much as possible. If motion detection is used as part of stage 2, two or more images are processed sequentially. Stage 2 involves the extraction of a ship outline from its surroundings. The cleaned up image is filtered and the ROI is identified. System performance is highly dependent on finding an accurate ROI [23] location. Finding the correct ROI is a difficult task, and even with simple backgrounds, errors often result in wrongly classified ships. First, background subtraction is attempted. Then, motion detection is used whenever possible to reject parts of a scene which do not change in successive frames. However, this is not reliable as a ship may travel too slowly. In addition, histogram projection may be used to assist ROI identification. ROI identification on SAR images is relatively easy compared to optical images because the ROI could be obtained by simple thresholding. The sole work on optical images by [12] uses background subtraction but this technique requires frequent updating of the reference background due to frequently changing lighting conditions. In our system, we have experimented with background subtrac-tion, frame differencing, histogram projection and thresholding but we will also explore other techniques in the future.

Stage 3 performs feature extraction. Our intention is to propose a camera operating on a low-bandwidth link long-range radio links with a data rate in the kilobits per second range. Therefore, we elected to use Hu's moment invariant method as it involves the evaluation and subsequent transmission of only 7 parameters from the camera to the classifier. The classifier will be located at a server which contains the generative model from the training phase. This arrangement minimizes the memory and communications requirements on the smart camera.

Using the software to simulate classification on the server since the software allows the experimentation with several classification algorithms [21]. Comparing the simple *k*-NN classifier against several classifiers of higher complexity. The results are shown in Table I. In each classifier twice with a minimum fold of 3 and a heurestically optimum fold of 10.

Classifiers List

S.No	Classifier	Folds
1.	*k*-NN (*k*=1)	3 10
2.	*k*-NN (*k*=3)	3 10
3.	*k*-NN (*k*=5)	3 10
4.	Support Vector Machine	3 10

5. Experiments

We are planning to conduct our experiments using a PC with a Pentium 4 CPU 1.8 G with 1-GB memory, and they involve the following two image data sets.

Data Set 1: This data set consists of Camera images.

Data Set 2: This data set includes ship candidate sub images obtained by ship candidate extraction from the images in Data set 1.

6. Conclusion

Because of the Security problem, in this approach am going to test the method on 3 different databases. First database is about 2000 frames of the sea targets from several mainstreams movies. The second database is collected from different military websites and the third one is database from low quality movies filmed by one of famous military companies for sea target detection purposes. It is obvious that because of observing framing rules the third database has the best result. This paper proposed a smart camera based maritime surveillance system. Smart cameras could complement existing surveillance methods with advantages in cost, size, power and size. Hu's moment invariants is a viable algorithm for implementation on smart camera based recognition system on the condition that the silhouettes must be properly generated. Further work needs to be done on accurate ROI localization and segmentation; increasing the training set size; and hardware implementation of the smart camera.

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