Sea Object Detection Using Colour and Texture Classification

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Abstract— **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. This paper focuses on the issue of ship detection from spaceborne optical images (SDSOI). Although advantages of synthetic aperture radar (SAR) result in that most of current ship detection approaches are based on SAR images. But disadvantages of SAR still exist. Such as the limited number of SAR sensors, the relatively long revisit cycle, and the relatively lower resolution. To overcome these disadvantages a new classification algorithm using colour and texture is introduced for Ship detection. Colour information is computationally cheap to learn and process. However in many cases, colour alone does not provide enough information for classification. Texture information also can improve classification performance. This algorithm uses both colour and texture features. In this approach for the construction of a hybrid colour-texture space we are using mutual information. Feature extraction is done by the co-occurrence matrix with SVM (Support Vectors Machine) as a classifier. Therefore this algorithm may attain a very good classification rate.**

Keywords— **ship detection from spaceborne optical images, synthetic aperture radar, Support vector machines classifier, Co- Occurrence Matrix, Hybrid Colour, Hybrid colour-texture**

I. Introduction

Ship detection 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 detection has become much more important for effective and efficient ship monitoring to prohibit illegal fishing activities in time.

However, ship detection based on SAR has limitations. First, with a limited number of SAR satellites, the revisit cycle is relatively long and, then, cannot meet the needs of the application of real-time ship monitoring. Second, the resolution of most satellite SAR images is often not high enough to extract detailed ship information.

Ship detection based on satellite optical images can partly overcome the aforementioned shortcomings of ship detection based on SAR and is complementary to SAR-based ship detection. Thus, it is advantageous to investigate SDSOI to better satisfy the requirements of ship monitoring. There are not many researches about target detection in sea through direct image processing and among them papers that utilize colour features are even fewer. For this reason almost all of the existing approaches suffer from one or more drawbacks like sensitivity to different sensors or invalidity for low SNR images . Many papers have worked on ship detection based on SAR2 images [5]. A new method based on combinatorial improved PNN3 model for ship detection in SAR imagery and [4] 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 [10]. Marivi et al [11] proposed a ship target detection method of SAR images by means of the discrete wavelet transform, taking advantage of the difference of statistical behaviour of the vessels and the sea. All above methods are dependent on SAR images; they 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 [6]. 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 harbour. One of the few researches that uses colour feature, from Lab colour coordinate system, for sea target detection is [9]. 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 new hierarchical cluster merging algorithm for image segmentation and applied it to the ship detection 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 [8]. One of the papers that have more superiority to previous works in visible images domain is [7]. 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 [8] 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 analysing several frames for exact results. So it is still important to find new methods of detecting target from sea background. Except [9] all above researches have worked on grey level images and for sure our method is one of the few one that utilizes colour feature for sea target detection.

The aforementioned works on target detection in sea appear to justify the implementation of the new colour space to find targets in the sea. From our previous experiments we know that linear transformation cannot satisfy clustering criteria in target detection domain. So in this paper quadratic transformation is introduced which is a new work in creating the new colour space. Creating an optimum connection between one of the most common clustering methods which is the FCM classifier, and the PSO search method is another motivation. All these points encourage us to present the target-based colour space (TCS) for suitable sea target detection. This paper is organized as follows. Section I provides learning colour and texture features using histograms. Section II provides combining colour and texture features for classification. Section III provides hybrid colour-texture space construction. Section IV provides Support vector machines classifier. Section V is about conclusion.

II. Learning Colour and Texture Features

A. Colour Feature

Colour information is readily available as input from a colour camera so no extra processing is required. Colour of a pixel is represented as a vector in the Red, Green, Blue (RGB) colour space or Hue, Saturation, Value (HSV). Real world surfaces often have more than a single colour. They are either white, pink, gray, or black. To learn the colour appearance of a real world surface, the histogram method is often used. A normalized histogram H approximates the distribution of colours in an image patch P, each bin in H is calculated by

$$Hi = ni/N \qquad (1)$$

where ni is the number of pixels whose colour falls into the region defined by bin i and N is the total number of pixels in P. When histogram is used for classification, during the training stage, a set of model histograms of a class is learned. In classification stage, a sample histogram is compared with the model histograms. The sample's class is assigned with the best matched model's class.

B. Texture Features

Although there is no formal definition of texture, the texture of a visual surface can be thought of as spatial distribution of intensity/colour variations. In the case of co-occurrence matrix, the performance depends on the number of gray levels, displacement sets are used. Texture is used to improve the performance of a colour based classifier but with a consideration of computational speed and memory requirement. A good tradeoff between performance improvement and added complexity is desired. For this reason, two texture learning methods were chosen: the Local Binary Pattern (LBP) method and a statistical method using 8 histograms of the intensity difference between two pixels at 2, 4, 6, and 8 pixels apart at horizontal and vertical directions. These two methods are significantly less complex than other texture methods. The LBP contains local intensity pattern of a pixel. The LBP of pixel n with intensity x is defined as:

$$lbp\ (n) = \sum_{i=1...8} 2^{bi(x-x1)} \qquad (2)$$

$$b_i(x) = \{1 \text{ if } x \geq 0, 0 \text{ if } x < 0. \qquad (3)$$

where x1...8 are the intensity values of the 8 pixels neighbouring n.

III. Combining Colour and Texture Features

A. Partitioning Training Set using Colour Histograms

From initial tests of the colour based classifier, it was found that the average performance was relatively good. The Colour information is rich enough in most cases. Classification errors arise when the sample images were taken under bad illumination condition when there were targets with very similar colour appearance to the path (even to a human eye). It is noted that extracting texture features is several magnitude more complex than extracting colour feature. From these observations, algorithm was built that uses colour as the primary feature and only consider texture feature in special cases where it is difficult to use colour to discriminate. Instead of having one threshold for each model colour histogram, two thresholds are learned. One high threshold is used to determine if a sample is matched with a model, one low threshold used to determine if it is not. If the intersection value falls in between these two thresholds, the texture feature is used. The samples that fall in this region are the difficult cases for the colour classifier.

B. Classification using Colour and Texture

During classification stage, the algorithm maps a pixel patch of unknown class label to either targets or non-targets. A patch is labelled as path if it's colour histogram is matched with any of the h colour histograms saved from the learning stage using the high threshold. If none of the model histograms matches with the sample, the algorithm iterates through the h models again. This time the intersection value between the sample and the model colour histogram is compared with the low threshold. If a matched model is found, the sample's texture histogram is compared with the model's texture histograms. A pseudo-code of the algorithm is listed below

for *i* = 1 to h do
if *M*(*sco*,*mco*,*i*) > *high thresholdi* then
s is path
return
end if
end for
for *i* = 1 to h do
if *M*(*sco*,*mco*,*i*) > *low thresholdi* AND
  M(*stx*,*mtx*, *i*) > *texture thresholdi* then
s is path
return
end if
end for
s is non path

sco, *stx* are the sample's colour and texture histogram, *mco*,*i* and *mtx*,*i* are colour and texture histogram of the *ith* model.

IV. HYBRID COLOUR-TEXTURE SPACE CONSTRUCTION

A. Colour Spaces

The construction of the hybrid colour-texture space starts with transforming a classified image, initially represented in the RGB standard system, into different colour spaces. Colour can be divided into four families [4] namely:

1. The primary spaces which are based on the trichromatic theory assuming that it is possible to match any colour by mixing appropriate amounts of three primary colours.
2. The perceptual spaces which try to quantify the subjective human colour perception using the intensity, the hue and the saturation.
3. The luminance–chrominance spaces where one component represents the luminance and the two others the chrominance.
4. The independent axis spaces resulting from different statistical methods which provide as less correlated components as possible.

a global colour space *Cs* gathers the components chosen for our approach, with *NCs* =30 vectors:
Cs={R,G,B,r,g,b,X,Y1,Z,x,y,z,L,a,b,u1,v1,c,h,H,S,V,Y,i,q ,u2,v2,I1,I2,I3}

The colour study is associated with texture analysis, by calculating 2 statistical parameters and 5 parameters of Haralick of the co-occurrence matrix.

B. Gray-Level Co-occurrence Matrices

Let *E* denote the space of candidates attributes. The number of attributes of *E* is *7 x 30 =210*, where *7* represent the five parameters of Haralick + the two statistical parameters, and *30* is the number of colours components. From *E* we select the attributes that will Compose the hybrid colour-texture space using mutual information.

C. Mutual Information

Mutual information (*MI*) is the measure of the dependence between random variables. The *MI* of two discrete variables *x* and *y* is defined based on their joint probabilistic distribution *p(x, y)* and the respective marginal probabilities *p(x) and p(y):*

$$\mathrm{MI}(x,y)=\sum_{i,j} a\log(a/b) \qquad (4)$$

$a= p(x_i,y_j)$, $b=p(x_i)p(y_j)$

The estimation of the joint probabilistic distribution p(x, y) represents the principal difficulty for the use of *MI*. Various methods have been studied in the literature to estimate such joint distribution (histograms and kernel-based methods). Authors in propose a fast method to estimate the *MI*. One of the advantages of this method is that it based in the estimation of the entropy. The relation between *MI* and the entropy can be defined as :

$$MI(x, y) = H(x) - H(y \mid x) \qquad (5)$$

Using the properties of the entropy, the mutual information can be rewritten into

$$MI(x, y) = H(x) + H(y) - H(x, y) \qquad (6)$$

This entropy is calculated using *k*-nearest neighbour method. This method has a second advantage. It allows the calculation between a set of features *x* and the output variable *y*.

D. Hybrid Colour-Texture Space

In this part, an algorithm will select the attributes composing the hybrid colour-texture space. These attributes are chosen from the space of candidates attributes *E*. The algorithm based on the mutual information is developed. It works in two steps. In the first step, the forward phase, attributes are adding one by one. At each iteration, the attribute selected to integrate the current subspace is the one that most increases the mutual information with the output variable. The forward phase is stopped when adding any new attribute decreases the mutual information. The second step is the backward phase. Attributes are eliminated one at time. The attribute that most increase the mutual information when it is discarded is eliminated from the subset of features. As in the forward step, the backward phase is stopped when discarding any other attributes decreases the mutual information of the subspace with the output variable. The final subspace is the hybrid colour-texture space. It contains the attributes that are the most discriminate.

V. Support Machine Vector

Among the methods with kernels based on the statistical learning theory of Vladimir Vapnik, SVM are the most known.SVM is a method of binary classification by supervised learning, it was introduced by Vapnik in 1995 . This method is an alternative to the recent classification. This method relies on the existence of a linear classifier in an appropriate space.

A. SVM Classifier

Support Vector Machine Algorithm are attractive, especially for non-linearly separable problems, where the problem is high-dimensional. A classification task usually involves with training and testing data which consists of some data instances. Each instance in training set contains one "target value"(class labels) and several "attributes"(features).The goal of SVM is to produce a model which predicts target value of data instances in the test set which are given only the attributes. It provides a Novel means of classification using the principles of structural risk minimization (SRM). It is one of the most sophisticated nonparametric supervised classifiers available today, with many different configurations depending upon the functions used for generating the transform space in which the decision surface is constructed. Here the classification problem is restricted to consideration of the two-class problem without loss of generality. In a binary classification task, the aim is to find an optimal separating hyper-plane. Considering the example shown in fig.1,there are many possible linear classifiers that can separate the data, but there is only one that maximizes the margin(maximizes the distance between the hyper-plane and the nearest data of every other class).

Only those vectors that are on the perimeter of the data cloud are used to determine the boundary. In other words, those data vectors, which are closest to the separating margins in the transformed space, are called the support vectors (SV).

Since this is a problem of classification of two classes, this method uses a set of learning data to learn the parameters of the model. It is based on the use of so-called kernel function that allows an optimal separation of the data. It was successfully evaluated on pattern recognition problem. For example in two classes problem(positive and negative sets of simples), the basic form of linear SVM classifier try to find an optimal hyperplane that separates the set of positive samples from the set of negative samples. The LIBSVM package that support multi-class problem available on to classify the different textures is used in our work.

VI. Experiments

Our experiments were conducted 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 spaceborne optical images, about $2000 * 2000$ pixels in size, with a total of 232 images and a resolution of 5–20 m. Typical samples are shown in Fig. 1. It is used to test our proposed approach of ship detection. For simplicity, all of the images were scaled to the spatial resolution of 10 m to train only one classifier in our experiments.

Data Set 2: This data set includes more than 600 typical ship candidate sub images obtained by our ship candidate extraction from the spaceborne optical images in Data set 1. Some typical samples are shown in Fig. 2. The aim is to test the performance of the presented hierarchical classification approach, which is a very important section of the ship detection approach.

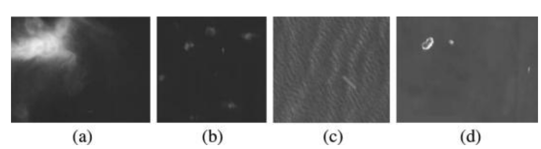

Fig. 1. Typical sea images. (a) Images with large clouds. (b) Images with small clouds. (c) Images with strong ocean waves. (d) Images with small islands.

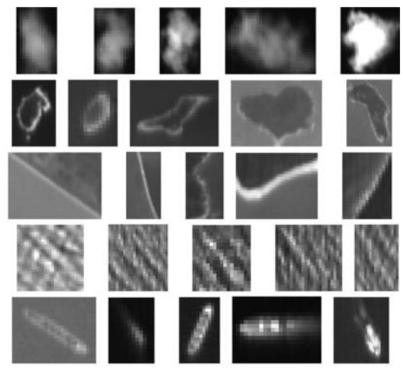

Fig 2: Typical samples in Data set.

VII. CONCLUSIONS

Because of the security problems sea target databases, unlike face and skin images, are not published. Lack of famous color images for sea target detection, forced us to create our own database. I 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.

An efficient classification algorithm for obstacle detection that combines colour and texture features were presented to detect ship in the sea . The Hybrid colour-texture space was constructed for classified image using mutual information. Thus the algorithm may achieve good classification rate when compared to existing algorithms.

REFERENCES

[1] Changren Zhu, Hui Zhou, Runsheng Wang, and Jun Guo “A Novel Hierarchical Method of Ship Detection from Spaceborne Optical Image Based on Shape and Texture Features”, *IEEE Transactions On Geoscience And Remote Sensing*, vol. 48, pp. 3446-3456, Sep. 2010.

[2] Saeed mirghasemi, Hadi Sadoghi Yazdi, Mojtaba Lotfizad, “Linear and Quadratic PSO Based Colour Space Conversion for Sea Target Detection”, *International Journal of Computer and Electrical Engineering*, vol. 2, pp. 1793-8163, Feb. 2010.

[3] Saeed Mirghasemi – “Sea Target Detection Based on SVM Method Using HSV Colour Space”, *IEEE Students Conference on Research and Development*, Nov. 2009.

[4] Shi-qi Huang, Dai-zhiLiu, Gui-qingGao, Xi-jianGuo , "A novel method for speckle noise reduction and ship target detection in SAR images", *Science Direct, Pattern Recognition*, pp. 1533-1542, Oct. 2010.

[5] Zhenhong Du, Renyi Liu, Nan Liu, Peng Chen, "A New Method for Ship Detection in SAR Imagery based on Combinatorial PNN model", *IEEE First Int. Conf. on Intelligent Networks and Intelligent Systems*, pp. 531-534, 2008.

[6] Yonggang Hu, Yi Wu, "Number Estimation of Small-Sized Ships in Remote Sensing Image Based on Cumulative Projection Curve", *IEEE Int. Conf. on Audio, Language and Image Processing, (ICALIP)*, pp. 1522-1526, July 2008.

[7] Shaoqing Yang, Sihua He, Hongwen Lin, "Video Image Targets Detection Based on the Largest Lyapunov Exponent", *IEEE The 9th Int. Conf. for Young Computer Scientists*, pp. 2973-2977, Nov. 2008.

[8] Sihua He, Shaoqing Yang, Aiguo Shi, Tianwei Li, "A Novel Image Moving Sea Targets Detection Method Based on Natural Measure Feature", *IEEE Int. Symposium on Information Science and Engineering*, pp. 397-400, Dec. 2008.

[9] Zhiling Hong, Qingshan Jiang, Heshan Guan and Fangfei Weng, "Measuring overlap-rate in hierarchical cluster merging for image segmentation and ship detection", *Fourth Int. Conf. on Fuzzy Systems and Knowledge Discovery (FSKD)*, vol. 4, pp. 420-425, 2007.

[10] Marivi Tello, Carlos Lopez-Martinez, Jordi J. Mallorqui, Ramon Bonastre, "Automatic Detection of Spots and Extraction of Frontiers in SAR Images by Means of the Wavelet Transform: Application to Ship and Coastline Detection", *IEEE Int. Con. on Geoscience and Remote Sensing Symposium*, *IGARSS*, pp. 383-386, Aug. 2006.

[11] T. Marivi, L. M. Carlos, and J. M. Jordi, “A novel algorithm for ship detection in SAR imagery based on the wavelet transform”, *IEEE Geoscience And Remote Sensing Letters*, vol. 2, pp. 201-205, April 2005.

[12] Hassan EL MAIA, Driss ABOUTAJDINE, Ahmed HAMMOUCH, “Colour-texture analysis by mutual information for multispectral image classification”, *IEEE Pacific Rim Conference on Communications, Computers and Signal Processing*, pp. 359- 364, Aug. 2009

[13] H.El Maia H, A.Hammouch, D.Aboutajdine, “Hybridization of the colour information with the texture by using the mutual information for the classification of satellite images”, *Int. Conference on Multimedia Computing and Systems (ICMCS)*, pp. 372-376, Apr. 2009.