Saliency based algorithm for ship detection in infrared images

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***Abstract*— In this paper we have worked on the problem of automatic ship detection in IR images. Segmentation of IR ship images is always a challenging task because of the intensity inhomogeneity, sea clutters and noise. In our proposed approach, we have shown that efficiency and accuracy of IR ship detection algorithms can be enhanced by only searching around the salient parts of the input image. In order to identify most salient regions, at first we computed the saliency map of the input image using the Graph-Based Visual Saliency (GBVS) algorithm. Next a multilevel thresholding of the saliency map is performed to get the ranked salient regions of the input image. By using the ship size as prior information, top-k regions are further processed to get the fine segmentation of the target. For this purpose we have used spatial constraint based fuzzy c-mean (FCM) segmentation algorithm along with a strategy to choose the cluster selection threshold. Experiments are performed on a data set of 18 diverse and challenging IR ship images, collected from different sources. Results show that our proposed framework is very effective and perform better compare to the methods which directly search the target in entire image.**

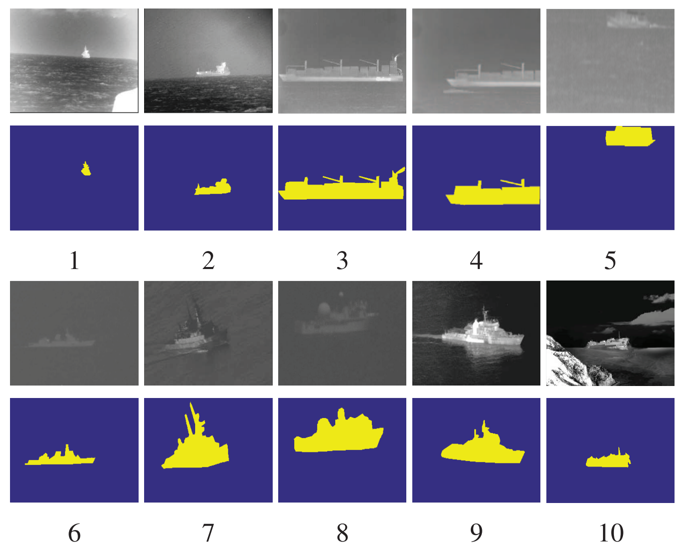

Fig. 1. Examples from IRShips data set.

I. Introduction

Infrared (IR) imaging systems have become very popular in military and civilian equipments because of the entirely passive detection in which source of radiations is the object itself [1]. Military applications includes target acquisition, surveillance, homing and tracking, and night vision, while non-military applications includes public surveillance, remote temperature sensing, thermal efficiency analysis, weather forecasting, spectroscopy, and environmental monitoring [1][2]. In recent years, IR systems have also attracted much attention in maritime security and traffic monitoring [3]. In this domain segmentation of IR ship images is one of the key and challenging step which guides the following recognition and tracking tasks. In this paper, we focus on the problem of IR ship image segmentation under different challenging conditions such as presence of sea sky line.

Ship detection in infrared images is full of challenges because of the limitation of IR imaging technology and variations in the sea states. At first IR images are characterized by low signal-to-noise ratio (SNR), low target-to-background contrast, lack of details, and intensity inhomogeneity due to uneven heating of different parts such as engine and chimney [1]. Secondly, the effects of sky reflections, emissions from surface waves and atmosphere, sea clutter, and large imaging distance, degrades the quality of the resulting image [4]. Critical requirement of the precise segmentation of IR ship image in the presence of all above challenges is the main motivation for our work.

The contributions of our work are three-fold. First, we have proved that speed and accuracy of IR ship detection algorithms can be enhanced by only searching around the salient parts of the input image. Second, we propose a region based segmentation method based on spatial constraint based fuzzy c-mean [5] algorithm. Third, we evaluate the performance of proposed framework on IR ship detection in challenging images. Because of the lack of availability of IR ship images data, we introduce a new challenging IR ship dataset *IRShips*, which consists of 18 images with presense of above mentioned challenges. Some example images in the IRShips dataset are shown in Fig. 1.

The remainder of this paper is organized as follows. We discuss related work in Section 2. In Section 3, we review the Graph-Based Visual Saliency (GBVS) [6] and fuzzy c-mean [7]. After that in Section 4, we present our proposed salient-region based IR ship detection framework. Finally, Section 5 concludes the paper by presenting experimental evaluations.

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II. Related work

To deal with the problem of segmentation of IR ship images, different methods have been proposed in literature. These include methods based on, thresholding [8], clustering [5][9][7], active contour [10] and neural networks [11]. Thresholding based methods are preferred for IR image segmentation because of their simplicity and efficiency. Popular thresholding based algorithms are generally based on classical methods such as Otsu's [8], minimum error thresholding [12] and entropy-based thresholding [13]. A comprehensive review of different thresholding techniques can be found in [14]. Thresholding methods do not consider the spatial relationship of the ship target and the sea background which results in non-uniform segmentation. In order to overcome this limitation, several extensions are proposed which incorporates local spatial information along with statistical properties [15]. However these methods fail to find the optimal threshold when the target is small compared to the background and when the contrast of the image is low, which is typically the case in IR ship images.

FCM [7] and mean shift [16] are among the popular clustering techniques used for IR ship image segmentation. Mean shift segments the image by iteratively merging the local regions. This may wrongly merge the target pixels into its neighborhood background when the boundaries between target and background are not clearly defined and when the size of the target is small. FCM [7] is a classical clustering method, which has shown promising results in the field of IR ship image segmentation. Similar to thresholding methods, spatial information can also be incorporated in the FCM clustering to make it more robust for ship detection [5]. Recently, [9] further improved the accuracy of FCM clustering by using the non-local spatial information based on the ship target. Accuracy of image clustering techniques suffers due to the presence of noise such as sea clutter and sky reflections. In order to overcome this problem, we propose a region based segmentation strategy, where search is performed only in the high target areas. This results in improved performance and speed up the whole segmentation process.

The active contour (AC) model exploits the topological structure of the ship target and is based on the curve evolution and geometric flows. The ChanVese model [10] has been successfully used in many applications of image segmentation. In IR ship images usually background and target regions are inhomogeneous which increases the difficulty of extracting the topological structure of the ship target. To overcome this weakness, [17] propose a a novel active contour model which is driven by the local image fitting energy and performs well on images having inhomogeneous intensities. Despite the robust segmentation ability, performance of AC based techniques greatly depends on the initial seed region.

Hopfield neural network (HNN) are also used for segmentation of IR images [11]. These methods are less popular because of the slow convergence of the optimization parameter selection process. Our work is also related to the [18], where an iteration based segmentation method for IR ship image segmentation is proposed. Like other thresholding based algorithms, this method also suffer because of the dim target and low contrast of IR images. Finally our work is also inspired from [19], where intensity and spatial features are combined using fuzzy inference system (FIS). Similar to our proposed framework, to extract spatial features, [19] also uses graph-based visual saliency (GBVS) algorithm [6] with a region growing technique.

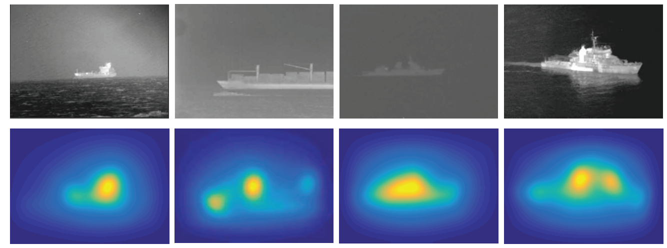

Fig. 2. Examples of GBVS maps of different IR ship images.

III. Image saliency and segmentation methods

As discussed in section II, FCM [5] is a widely used method for IR ship image segmentation. In this section we review this segmentation method along with Graph-Based Visual Saliency (GBVS) algorithm for extracting the most salient regions in the IR image.

A. Graph based visual saliency

Saliency is defined as the distinctiveness of features. Saliency maps shows the image regions, where rare or informative features can be found, depending on the definition of saliency. High saliency regions correspond to objects, while lower saliency is associated to background. A distributed graph-based solution called Graph-Based Visual Saliency (GBVS) is proposed in [6]. The objective is to find saliency values at each pixel depending on the entire image plane rather than relying on local information. Fig. 2 shows some examples of saliency maps for different IR ship images. As shown in Fig. 2, we are using GBVS algorithm to highlight the target region and to minimize the effect of features belonging to the background region on target detection, which can mislead the target detection & recognition algorithm.

Given an image $I(x,y)$, we want to find the salient regions in the image. Like the leading models of visual saliency, GBVS algorithm consists of three steps: First feature extraction from the input image, second forming activation maps on various feature channels and finally normalizing the activation maps in a way, which highlights prominent areas in the image and admits the combination with other maps. These three steps are further explained as follows.

1) Feature Extraction:: In the first stage, n different filters F_n are applied to the input image $I(x,y)$ to get various features maps M_n.

$$M_n\left(x,y\right) = F_n\left\{I\left(x,y\right)\right\} \quad (1)$$

Where F_n are filters depending upon the feature to be calculated. For IR ship images, we can compute contrast, edge orientation and intensity features. Some other features such as color and motion features can be computed from multi-band images & videos.

2) Activation Maps:: Given a feature map $M_n(x, y)$, our objective is to compute an activation map, such that high values of activation map are obtained at locations, where $M_n(x, y)$ is dissimilar to its neighbors. Now consider the fully connected directed graph G_A, made by connecting every node of the lattice M_n, labeled with two indices (x, y) with all other nodes. The weight value w_1 of the directed edge from node (x, y) to node (p, q) can be calculated as follows.

$$\omega((x,y),(p,q)) \triangleq d((x,y)\|(p,q)) \cdot F(x-p, y-q), \quad (2)$$

where $d((x,y)\|(p,q))$ and $F(x-p, y-q)$ are given as:

$$d((x,y)\|(p,q)) \triangleq \left|\log \frac{M_n(x,y)}{M_n(p,q)}\right| \quad (3)$$

$$F(a,b) \triangleq \exp\left(-\frac{a^2+b^2}{2\sigma^2}\right) \quad (4)$$

where σ is a free parameter, and is usually set as one tenth to one fifth of the map width. Now we can define a Markov chain on G_A by normalizing the edge weights to unity and drawing an equivalence relationship between nodes & states and edge weights & transition probabilities. The equilibrium distribution of this chain accumulates mass at nodes that have high dissimilarity with their neighboring nodes.

3) Normalization and Combination:: The goal of this step is to concentrate the mass on individual activation map prior to adding different feature maps. After the normalization each activation map has high values clustered together at few locations. Now we can get weighted average of different activation maps, where weights given to each activation map depends on the type of salient regions to be detected.

B. Spatial FCM

Suppose we have a set of feature vectors $X = (x_1, x_2, \ldots x_N)$, where each $x_i \in \mathbb{R}^d$. Our goal is to partition the feature space into C clusters having cluster centers $(\mu_1, \mu_2, \ldots \mu_C)$. For a typical IR ship image with N pixels, we have $d = 1$, *i.e.*, x_i is the intensity value of each pixel. Number of clusters is an experimental parameter and in our study we suggested to use a value $>= 3$ by considering the presence of sky, sea background and ship target in IR ship images. The standard FCM [7] works by iteratively minimizing the following cost function:

$$J_{FCM} = \sum_{i=1}^{N}\sum_{j=1}^{C} \alpha_{ij}^m \|x_i - \mu_j\|^2, \quad (5)$$

α_{ij} represents the fuzzy membership or probability of pixel x_i in the jth cluster, where $\alpha_{ij} \in [0,1]$ and $\sum_{j=1}^{C} \alpha_{ij} = 1$. $||.||$ is the Euclidean distance between the pixel x_i and center μ_j of the jth cluster. m is the fuzziness control parameter and is usually set as 2. Starting from an initial guess for cluster centers μ_j, FCM iteratively minimize the cost function by following update equations:

$$\alpha_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\|x_i-\mu_j\|}{\|x_i-\mu_k\|}\right)^{2/(m-1)}}, \quad (6)$$

$$\mu_j = \frac{\sum_{i=1}^{N}\alpha_{ij}^m x_i}{\sum_{i=1}^{N}\alpha_{ij}^m}, \quad (7)$$

In spatial FCM [5] α_{ij} is modified by also incorporating the membership of corresponding neighbourhood of each pixal, according to following equations:

$$\beta_{ij} = \sum_{k\in\Omega(x_i)} \alpha_{kj} \quad (8)$$

$$\acute{\alpha}_{ij} = \frac{\alpha_{ij}^p \beta_{ij}^q}{\sum\limits_{k=1}^{C} \alpha_{ik}^p \beta_{ik}^q}, \quad (9)$$

where $\Omega(x_i)$ represents a square window typically of size 5×5, centered at pixel x_i. p and q are parameter to control the weight of the spatial β_{ij} and membership α_{ij} functions. In this way using spatial function effect of noisy pixels and low contrast, present in IR images can be greatly reduced whereas in case of homogeneous regions clustering remains unchanged.

IV. The Proposed Segmentation Framework

The flow of our proposed ship detection framework is shown in Fig. 3. Our approach can be divided into two parts, where in the first part we extract the region of interest (ROI) with the target included and in the second part we apply image segmentation algorithm within the ROI to extract the target. Details of the ROI selection and target detection procedure is discussed in the following sections.

A. Region extraction

Given an input IR ship image $I(x, y)$, having height H and width W, where $x \in (1, 2, \ldots, H)$ and $y \in (1, 2, \ldots, W)$. At first, saliency map $S(x, y)$ of the input image is computed using the GBVS algorithm discussed in section III-A. Next a rescaled intensity image is obtained by multiplying input image with the saliency map, to highlight the target region and to suppress the background clutter.

$$SI(x,y) = I(x,y) \times S(x,y), \forall\ x, y \quad (10)$$

Next a *P*-level thresholding of scaled intensity image SI is performed using Otsu's method [8]. As shown in Fig. 3, at this step we will get a hierarchy of salient regions $\{\gamma_1, \gamma_2, \ldots, \gamma_P\}$, where each subsequent region includes its preceding region. In this way we can either select the fix number of top-K salient regions or we can select them based on the ship size , which can be supplied as a prior information. Finally a convex hull of top-K regions is marked as the high target region and a binary image BI is obtained, in which pixels inside convex hull belong to the foreground. A bounding box of the target area in the BI image is computed and its coordinates are represented as: $BB = [TLx, TLy, BRx, BRy]$.

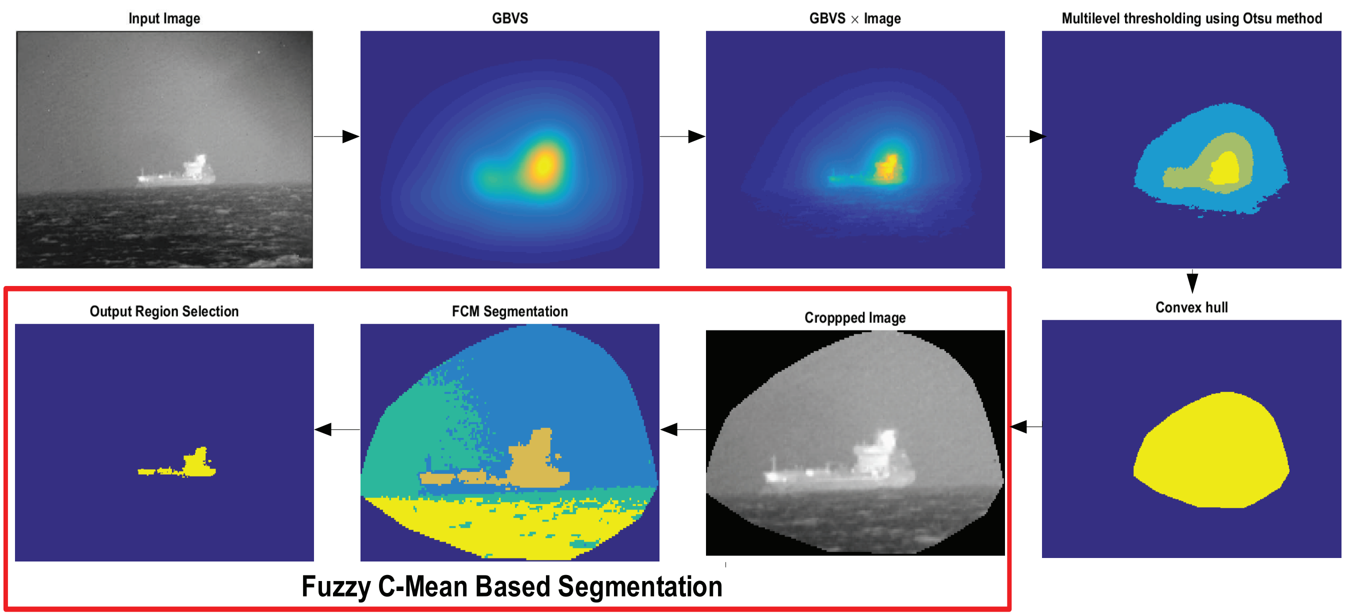

Fig. 3. Flow of the proposed IR ship detection algorithm.

B. FCM based segmentation

In order to perform segmentation and to extract ship from the target region, we used spatial FCM clustering algorithm discussed in section III-B. In the first step a portion of the input image is obtained by cropping it using the region bounding box BB of the BI image.

$$CI(i,j) = I(x,y), \forall\ i,j,\ where$$
$$x \in (TLx, \ldots TLx + BLx), y \in (TLy, \ldots TLy + BRy) \quad (11)$$

Similarly target binary image is also cropped using its region bounding box BB.

$$CBI(i,j) = BI(x,y),\ where$$
$$x \in (TLx, \ldots TLx + BLx), y \in (TLy, \ldots TLy + BRy) \quad (12)$$

Final search image is obtained by multiplying cropped input image and the cropped binary target image:

$$FI(i,j) = CI(i,j) \times CBI(i,j), \forall\ i,j \quad (13)$$

Next FI image is divided into a set of C clusters using the spatial FCM clustering algorithm [5], where $\{\Omega_1, \Omega_2, \ldots, \Omega_C\}$ represents the set of input image pixels belonging to different clusters. Note that search image FI pixels can be mapped back to the corresponding pixels in the input image I uisng the bounding box BB of the target area in the BI image. Next mean intensity μ value of each cluster region Ω is computed. Finally regions having mean intensity value greater than a cluster selection threshold τ are selected and merged to obtain the final segmented output image OI.

$$\begin{aligned} OI(x,y) &= BI(x,y), where \\ x,y &\in \{\Omega_1, \Omega_2, \ldots, \Omega_C\} \\ \mu(\Omega_i) &> \tau \end{aligned} \quad (14)$$

V. Experimental results

In this section we have presented different experimental results conducted on the IRships dataset. We have made comparisons between our proposed ROI base ship detection method and global search based algorithm. We compare our proposed region based FCM algorithm FCMR with the FCMI which is the application of FCM algorithm [5] directly on the whole image. All experiments were performed on an Intel Xeon processor, 2.4 GHz CPU, with 4 GB RAM.

Ship detection performance is evaluated using the standard measures *i.e.*, precision (P), recall (R) and F-score (F). Per-image precision is the probability of the correct classification of ship pixels. Per-image recall is the probability of the total ship pixels that are included in the segmented image. Precision, recall and F-score measures for an image, given its ground truth segmentation, are defined as:

$$P = \frac{TP}{TP+FP}, R = \frac{TP}{TP+FN}, F = 2((P)^{-1} + (R)^{-1})^{-1}, \quad (15)$$

where TP, FP and FN are the true positive, false positive and true negative (FP) rates, respectively.

In all experiments we used top-3 salient regions during the region extraction procedure described in section IV-A. For the proposed FCM based algorithm, discussed in section IV-B, we used $C = 3$ considering three possible segments in the image representing sea, sky and ship object. We used $\tau = 170$, which is a suitable cluster selection threshold for the IRships dataset and we have chosen this value experimentally. For all methods based on FCM, we used standard value of fuzziness control parameter $m = 2$ in equation 5. Finally, default values are used for all other parameters in FCM algorithm.

TABLE I
SHIP DETECTION RESULTS ON THE IRSHIPS DATASET.

	Avg. Precision	Avg. Recall	Avg. F-Measure	Avg. Speed(Sec)
FCMR	0.730	0.643	0.576	1.498
FCMI	0.588	0.536	0.445	2.843

TABLE II
PER-IMAGE PERFORMANCE OF FCMR AND FCMI ON IRSHIPS DATASET.

Image	Size	FCMR				FCMI			
		P	R	F	T	P	R	F	T
1	[227,320]	0.03	1.00	**0.06**	5.39	0.03	0.64	0.05	6.05
2	[218,320]	0.17	0.98	**0.29**	0.95	0.07	0.95	0.14	2.37
3	[234,320]	1.00	0.72	**0.84**	1.43	1.00	0.29	0.45	2.26
4	[267,320]	0.93	0.71	**0.81**	1.56	0.94	0.40	0.56	6.46
5	[128,335]	0.92	0.48	**0.63**	0.73	0.18	0.55	0.27	2.24
6	[193,320]	0.98	0.82	**0.89**	0.98	0.98	0.81	0.89	0.89
7	[193,320]	0.92	0.22	**0.36**	0.85	0.93	0.20	0.34	0.97
8	[194,320]	1.00	0.48	**0.65**	0.96	1.00	0.32	0.49	1.96
9	[195,320]	1.00	0.54	0.70	1.28	0.82	0.79	**0.80**	2.28
10	[256,256]	0.23	0.31	**0.26**	2.27	0.09	0.21	0.12	1.89
11	[227,321]	1.00	0.45	0.62	1.04	1.00	0.51	**0.68**	1.75
12	[220,320]	0.00	1.00	**0.01**	2.18	0.00	0.21	0.00	3.28
13	[192,320]	0.79	0.53	**0.64**	1.24	0.86	0.44	0.58	2.42
14	[233,320]	0.97	0.84	**0.90**	1.19	0.98	0.81	0.89	2.78
15	[193,320]	1.00	0.44	**0.61**	1.33	0.44	0.70	0.54	5.33
16	[226,320]	0.81	0.87	**0.84**	1.38	0.21	0.99	0.34	3.89
17	[189,320]	0.39	0.48	**0.43**	1.27	0.07	0.17	0.09	1.87
18	[190,320]	1.00	0.70	**0.82**	0.94	1.00	0.65	0.79	2.49

A. Dataset

There is a lack in open access availability of IR ship image datasets, such as the 200 IR images used in [18]. In order to fill this gap and to evaluate the performance of our proposed algorithm, we have collected a new challenging dataset IRships, which consist of 18 challenging IR ship images. These images were collected from different sources including FLIR and fixed ship-borne camera. These images include typical challenges in IR images, such as sky reflections in image 1 to 4 and sea clutter in images 7, 8 and 17. All images were cropped and scaled such that dimension of the largest side becomes 320 in case of width and 256 in case of height, which is the typical resolution of different IR cameras. A minimum side length of 128 is also ensured while maintaining the aspect ratio. For performance evaluation purposes, we have also labeled each image manually to establish the ground truth (GT) for each image. Thumbnail of example images along with ground truth can be seen in Fig. 1. Average dimensions of all images present in the dataset are 210×320, whereas sizes of individual images are shown in Table II.

B. IR ship target segmentation results

Table I presents the average performance comparison of FCMR and FCMI methods on the *IRShips* dataset. Average precision, recall and F-Score are reported along with average segmentation time of each algorithm. It can be seen that region based algorithm is better in terms of both accuracy and efficiency. FCMR has the average F-Score of 0.576, which is 13% better than the average F-score of image based algorithm FCMI *i.e.*, 0.445. Similarly execution time of FCMR (1.498sec) is better than the execution time (2.843sec) of its corresponding image based algorithm.. These results demonstrates the effectiveness of ROI based algorithm as compared to the image based algorithms.

Performance on the individual images is shown in Table II. Region based algorithm performed better on 16 images out of 18, as compared to image based technique. Overall on 2 images, performance of image based method is better than FCMR. In these images region based method also gave comparable performance *e.g.*, 0.68 vs. 0.62 on image 11. For images 9 and 11 image based methods performed better mainly because of of high contrast and less clutter.

Few examples of segmentation results using all tested methods are shown in Fig. 4. Image based technique fail when there is low contrast and clutter in the input image, for example rows 1, 2 and 5, in the Fig. 4. At times FCMR also gives over segmentation *e.g.*, rows 1, 2 & 8 in Fig. 4. This over-segmentation is the result of in-appropriate parameters such as number of salient regions and cluster selection threshold τ. These results can be improved further by matching the number of segments according to prior ship size and selecting threshold τ according to the contrast of the IR image. Finally when the image contrast is reasonable and there is less clutter in the IR image, all methods perform well, *e.g.*, rows 4, 6 & 7 in Fig. 4. From all above results, it can be concluded that searching only in the saliency regions improves the performance and reduces the effects of contrast and sea noises.

The proposed FCMR is an iterative segmentation method, hence selecting the appropriate number of iteration are critical for the successful segmentation. For FCM based methods we can compare the cost in equation 5 for two consecutive iterations and stop if the change is below a certain threshold. In our experiments, for the stopping criteria, we used standard value of 0.01 for the cost difference or maximum number of iteration of 100, whichever comes first. Finally, in order to choose an appropriate cluster selection threshold τ, we performed an experimental analysis to compare different threshold values. Average performance of FCMR method on IRships dataset with increasing number of cluster selection threshold is shown in Fig. 5. In case when there is no cluster with mean value above the threshold, we use only the cluster with the highest average intensity value. It can be seen that precision increases and recall decreases initially and become stable after certain threshold. This behavior shows that we can set an appropriate threshold value in FCMR algorithm for accurate ship detection in IR images.

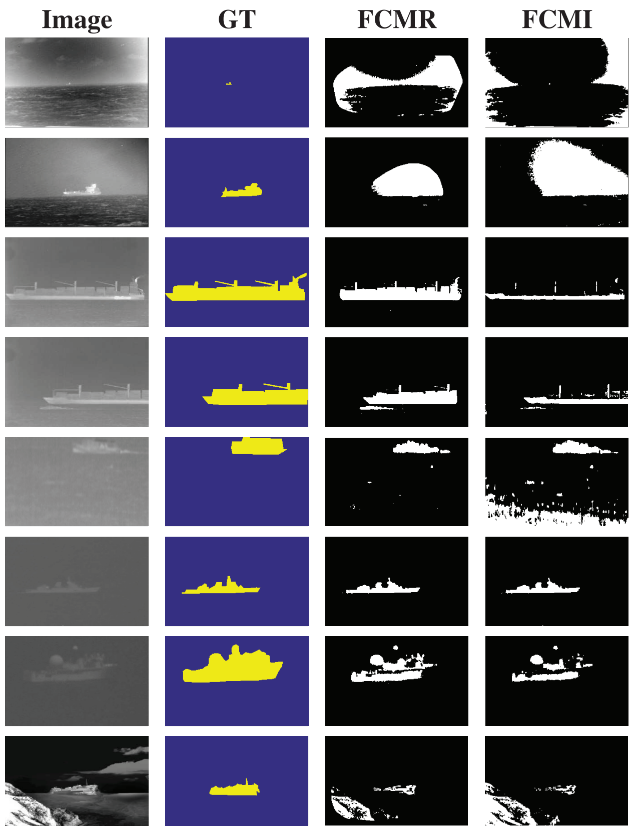

Fig. 4. IR Ship segmentation results of different methods.

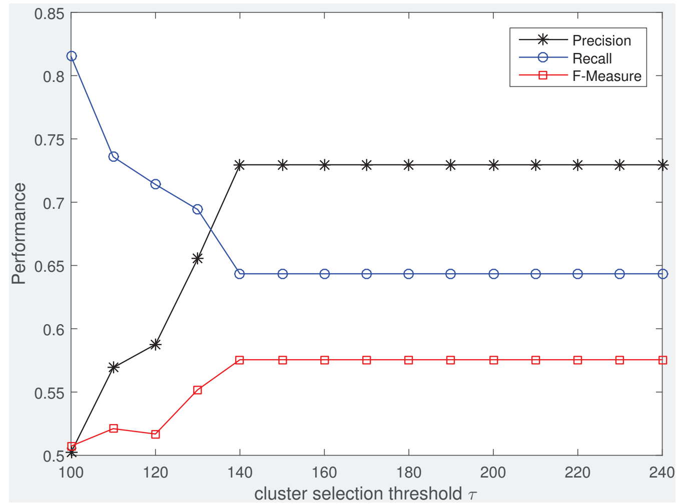

Fig. 5. Effect of cluster selection threshold τ on FCMR performance.

VI. Conclusion

In this paper we have proposed a region based framework for ship detection in IR images. A visual saliency algorithm for region selection is combined with existing state-of-the art image segmentation methods. A region based FCM algorithm (FCMR) is proposed, which is based on widely used fuzzy c-mean clustering method and GBVS saliency algorithm. Adaptive method for selecting the number of salient regions along-with threshold selection strategy for FCM algorithm is proposed. A dataset of challenging IR ship images is also presented and performance of different algorithms is tested. Experiments show that the region based search improved the performance and efficiency of ship detection as compared to the image based algorithms.

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