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Comparative Performance of Two 2-D Detectors in the Case of Multipixel Low Contrast Object on a Real Sea Surface

Maria Karen Gonzalez-Castillo
Facultad de Ingenieria
Universidad Autonoma del Carmen
Ciudad del Carmen, Mexico
m.karen@live.com.mx

Victor Golikov
Facultad de Ingenieria
Universidad Autonoma del Carmen
Ciudad del Carmen, Mexico
vgolikov@pampano.unacar.mx

Hussain Alazki
Facultad de Ingenieria
Universidad Autonoma del Carmen
Ciudad del Carmen, Mexico
halazki@pampano.unacar.mx

Oleg Samovarov
Ivannikov Institute for System Programming,
Plekhanov University of Economics
Moscow, Russia
samov@ispras.ru

***Abstract*—Much interest has arisen in the problem of automatic video detection of small low contrast floating objects on a sea surface. The Modified Matched Subspace Detector (MMSD) has been recently proposed for detecting a barely discernible object in an agitated sea surface. MMSD uses the intensity difference between the sea and the object at relatively high frequencies. In the literature the performances of this detector has been evaluated using only a sea model (additive Gaussian background clutter). In this paper we realize a comparison between classical Matched Subspace Detector (MSD) and MMSD using real sea images with synthetic model of the reflections from floating objects. This paper investigates the comparative MSD and MMSD performance, provided that the energy reflected from the object is equal to the energy reflected from the sea. The paper considers the dependence of the detection probability with a fixed probability of false alarm on the difference between the average of reflections from the sea surface and from a floating object at the different MMSD parameters and standard deviations of reflections from the object and the sea surface.**

***Keywords*—detection, real sea surface, multipixel object**

I. Introduction

Ship-based automatic video detection of small floating objects on an agitated sea surface remains a hard problem**.** Many detectors based on background subtraction have appeared to solve the detection in fluctuating backgrounds, as designed in [1] where neighboring pixels around a pixel are used to filter the disturbances that could affect a single pixel, which in a fluctuating background does not occur. The work [2] compares background subtraction with methods which consider temporal and spatial correlation, showing that those methods outperform the background subtraction when they are implemented in a fluctuating background. The works like [3] tried to improve the Mean Subtraction Filter (MSF) by designing the called Modified Mean Subtraction Filter (MMSF), but in all cases the results indicate that a high signal-to-background ratio (SBR) is required to achieve the high quality detection. The previous works [1], [2], [3] perform a filtering to reduce the background clutter or improve the target; however, to achieve detections with low SBR it is necessary that the filters act to improve the target and reduce the background clutter. Another type of the target detection algorithms is based on a statistical hypothesis test that is used in the case of a heavy dynamic background environment [4]. The well-known matched and matched subspace filters [4] are such algorithms. Several papers have addressed adaptive detecting schemes, such as the detection algorithm [5], adaptive generalized likelihood ratio test (GLRT) algorithm [6], and adaptive subspace detector (ASD) [7]. Usually, the detector estimates the local mean of background and then subtracts this value from a signal of each pixel. Assuming that the presence of a target changes the background power, the work [8] created the Modified Adaptive Subspace Detector (MASD) which combines ASD and adds a term that increases the dataset power when dark target is present. MASD and ASD are used by [9] to process images.

An optical detector for the maritime environment must be able to cope with an almost limitless set of scenarios. Aspects that can influence the performance of an optical detector include a water splashes, white caps on waves and sensor motion. The combination of these factors places the implementation of an optical detector in the maritime environment firmly in the domain of a “difficult problem”.

The common drawback of the published papers is the assumption that the background and channel noise are almost Gaussian processes without taking into account the above features of reflections from the real sea surface. In contrast of published papers [9, 10], this paper uses real images of the sea surface (under various conditions), on which an artificial object model is placed. In this case it is possible to change the difference between statistical parameters of the object and sea. The aim of this paper is to study the quality of two detectors (MSD and MMSD) when detecting low-contrast floating objects. The value of the contrast between reflections from the sea and from an object is understood as the values of difference of statistical estimates: average and standard deviation. The paper studies the dependence of the detection probability at a

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fixed false alarm probability on the difference between the average and standard deviations. Special attention is paid to the analysis of the quality of detection at the same average intensity of reflections from the sea and from the object. We show the advantage of the MMSD that allows to detect small floating objects on an agitated sea surface even with the same average and standard deviation of the reflected signals from the sea surface and the object.

II. MODEL OF REFLECTIONS FROM A FLOATING OBJECT

In this paper, unlike the previous ones, real videos of the sea surface will be used, in which an artificial model of a floating object is inserted. This approach allows you to change the parameters of the object model in order to assess the quality of detection for various types of objects. This section is devoted to the description of the used floating object model. The image to be analyzed is divided into square sub-images of size (K×M), which are analyzed in order to detect the object in them. We assume that the multipixel object of size (N×L) may be present completely anywhere in the sub-image of size (K×M).

The useful signal is modeled as a two-dimensional matrix (N×L), where N indicates the number of rows and L the number of columns. The signal model is a deterministic process unknown a priori. It is assumed that the floating object is solid and therefore its vibrations on the sea surface and the corresponding light reflections are limited to sufficiently low frequencies compared to reflections from the sea surface. The signal model of the object of r-th column-vector of the sub-image is represented by:

$$\boldsymbol{s}_r = \mathbf{H}\boldsymbol{\theta}_r, \tag{1}$$

where r = 1, 2, …, L, $\mathbf{H}$ is the object mode matrix (Vandermonde matrix) with discrete complex exponential elements:

$$\mathbf{H} = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ z_0 & z_1 & \cdots & z_N \\ \vdots & \vdots & \cdots & \vdots \\ z_0^{N-1} & z_1^{N-1} & \cdots & z_N^{N-1} \end{bmatrix}, \tag{2}$$

where $z_n^i = h_{in} = \frac{1}{\sqrt{N}} \exp\left(\frac{j2\pi in}{N}\right)$, the subscript n indicates the column number of the matrix $\mathbf{H}$ and the harmonic number n = 0, 1, 2, …, N-1. The variable i indicates the row number of the matrix $\mathbf{H}$ and the value at discrete time i = 0,1, 2, …, N-1. N is the number of values in each column, $j=\sqrt{(-1)}$. The unknown parameter $\boldsymbol{\theta}_r$ is the amplitude vector of the harmonics that locates the deterministic object signal in the signal subspace spanned by the p columns of a known target mode matrix. Taking into account that in real videos the power of the target fluctuates $\boldsymbol{\theta}_r$ is selected like a column vector with random values. It is used the uniformly (between zero and one) probability density function for this random value. The vectors $\boldsymbol{s}_r$ are grouped in a matrix with L columns which form the multipixel object.

III. PROBLEM FORMULATION AND DETECTORS

We will assume that the floating object model has dimensions (N×L) and the window in which the detection is performed has dimensions (K×M). Then in the case of N=K and L=M we can represent two statistical hypotheses H_0 and H_1 for the case of floating object detection in the sea:

$$\begin{cases} H_0 \colon \boldsymbol{x}_m = \boldsymbol{c}_m + \boldsymbol{n}_m \\ H_1 \colon \boldsymbol{x}_m = \boldsymbol{s}_m + \boldsymbol{n}_m, \end{cases} \quad m \in [1, M] \tag{3}$$

where $\boldsymbol{c}_m = [c_{1m}\ c_{2m} \cdots c_{Km}]^T$ is the background (sea) vector, $\boldsymbol{n}_m = [n_{1m}\ n_{2m} \cdots n_{Km}]^T$ is the channel noise vector, $\boldsymbol{s}_m = [s_{1m}\ s_{2m} \cdots s_{Km}]^T$ is the object unknown deterministic floating object vector. In this paper we assume that the value of p will always be less than K, since the floating object is a solid object, therefore, its fluctuations do not contain high frequencies, instead, the sea surface is about liquid, therefore, reflected light frequency can be high enough. We define the K×p matrix $\mathbf{H}_s = [\boldsymbol{h}_0, \boldsymbol{h}_1, \cdots, \boldsymbol{h}_{p-1}]$ and its corresponding object subspace $\langle \boldsymbol{H}_s \rangle$, which is the span of $\{\boldsymbol{h}_m\}_0^{p-1}$, where $\boldsymbol{h}_m = \frac{1}{\sqrt{K}}\left[h_{0m} h_{1m} \cdots h_{(K-1)m}\right]^T$. We next define the K×(K-p) matrix $\boldsymbol{H}_s^{\perp} = [\boldsymbol{h}_p, \boldsymbol{h}_{p+1}, \cdots, \boldsymbol{h}_{N-1}]$ and its corresponding subspace $\langle \boldsymbol{H}_s^{\perp} \rangle$, which is the span of $\{\boldsymbol{h}_m\}_p^{K-1}$. There is no energy from the object in this subspace. We assume that $\boldsymbol{H}_s$ and $\boldsymbol{H}_s^{\perp}$ are, respectively, full rank and that $\boldsymbol{H}_s^{\perp H} \boldsymbol{H}_s = \mathbf{0}$. Let $\boldsymbol{H}_s$ be K×p mode matrix with columns that contain the orthogonal basis vectors that span the object subspace, $p<K$. The object signal $\boldsymbol{s}_m = \boldsymbol{H}_s \boldsymbol{\theta}_m$ is the deterministic unknown signal of interest which belongs to a known subspace $\langle \boldsymbol{H}_s \rangle$ of size K×p, where the abundance vector $\boldsymbol{\theta}$ (size p×1) is unknown. The orthogonal subspace $\langle \boldsymbol{H}_s^{\perp} \rangle$ contains the columns from p to K-1.

We consider two detection algorithms synthesized by the GLRT method. The first algorithm (well-known MSD) is synthesized under the condition that the shape of the signal from the object is unknown, but the spectral frequency range is known. The second algorithm (MMSD) is recently synthesized under the condition that the frequency range is known in which the received signal power depends on the statistical hypothesis. The MSD is:

$$T_{MSD} = \sum_{m=1}^{M} \boldsymbol{x}_m^T \boldsymbol{P} \boldsymbol{x}_m \underset{H_0}{\overset{H_1}{\gtrless}} \eta, \tag{4}$$

where $\boldsymbol{P}$ is the orthogonal projection matrix onto the object subspace $\boldsymbol{H}_s$: $\boldsymbol{P}=\boldsymbol{H}_s(\boldsymbol{H}_s^H \boldsymbol{H}_s)^{-1}\boldsymbol{H}_s^H$, η is a threshold to be chosen according to the desired false alarm probability. The MMSD is:

$$T_{\mathrm{MMSD}} = \sum_{m=1}^{M} \left[\frac{\boldsymbol{x}_m^T \boldsymbol{x}_m}{K\sigma_0^2} - b \cdot ln \frac{\boldsymbol{x}_m^T \boldsymbol{P}_{\perp} \boldsymbol{x}_m}{K\sigma_0^2}\right] \underset{H_0}{\overset{H_1}{\gtrless}} \eta_1. \tag{5}$$

where $\boldsymbol{P}_{\perp} = \boldsymbol{I}\text{-}\boldsymbol{P}$ is the projection matrix onto the subspace orthogonal to object subspace, σ_0^2 is the background variance of the pixel, b is sensitive factor.

IV. COMPARATIVE PERFORMANCE ASSESMENT AND DICUSSION

In the following, we assess the performance of the MMSD and MSD both in terms of false alarm probability (P_{fa}) and detection probability (P_d). This paper uses 2D processing, i.e. for each frame, the detector makes an automatic decision on the presence or absence of an object. Theoretical analysis of the MSD shows that the MSD is sensitive to the ratio of the power of reflections from the object to the power of reflections from the sea. It is known that the signal power depends on the average and standard deviation of this signal. It is also that if the difference between the averages or standard deviations of the object and the sea decreases then the probability of the object detection decreases too. The MMSD is sensitive to the received signal power change inside the orthogonal subspace $\langle \boldsymbol{H}_s^{\perp} \rangle$. Further in this section it will be shown the experimental outcomes that have confirmed the high quality of the MMSD. In Figs. 1 and 2 show the power spectra of reflections from a typical object and the rough sea surface. The object has intense reflections at low frequencies (up to 1-2 Hz at 100 units), and the sea surface has intense reflections up to 7 Hz. Using these data, the value of the parameter p is selected in both detection algorithms.

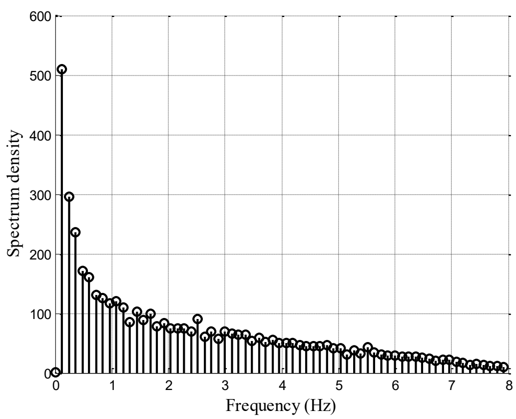

Fig.1. The small boat reflection average spectral density.

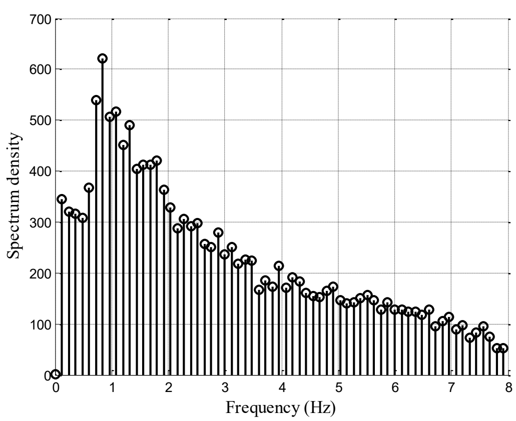

Fig.2.The sea reflection average spectral density.

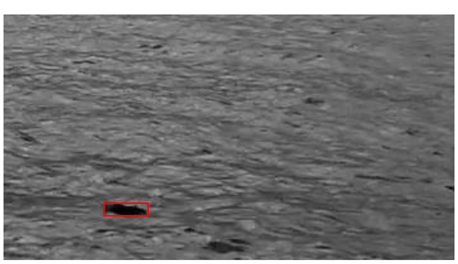

Fig.3 The sea with real floating object (marked with a red outline)

Fig. 3 shows the surface of an agitated sea with a poorly visible object. In practice, making a video with floating objects that have given parameters of mean and standard deviation, size, color, etc., is a very difficult task that requires large material costs. Therefore, in this paper, an artificially created floating object is used on the surface of a real sea, in which any parameters of the floating object are programmatically changed. (Dataset https://n9.cl/cce21).

Fig.4. Object model example

Fig.5. Object real example

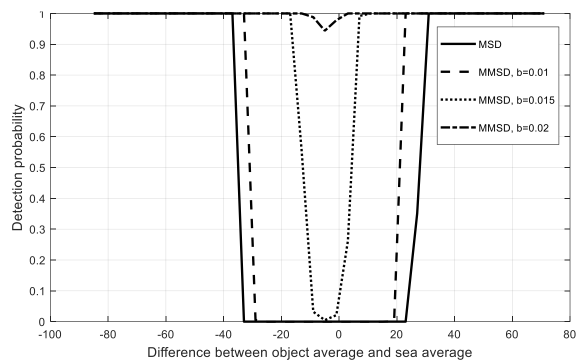

Fig.6. Detection probability vs difference between object average and sea average, NBR=0.005, OV/BV=1, p=8.

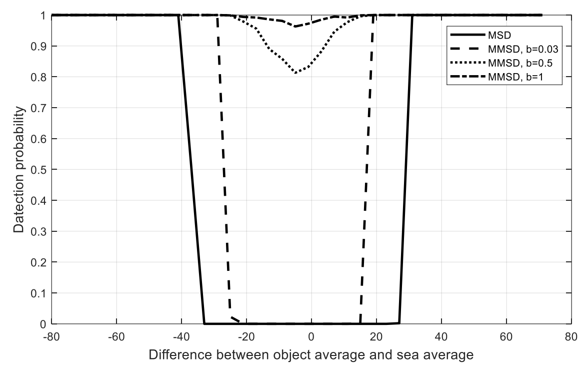

Fig.7. Detection probability vs difference between object average and sea average, NBR=0.005, OV/BV=1, p=4.

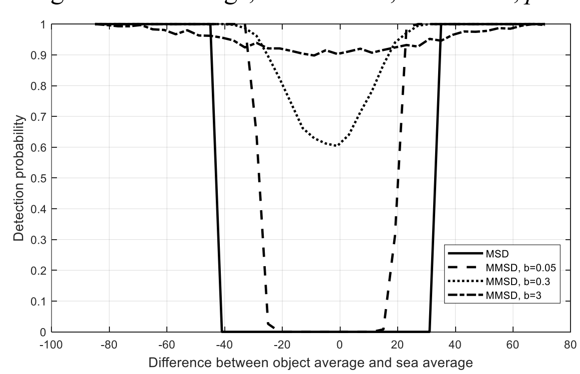

Fig.8. Detection probability vs difference between object average and sea average, NBR=0.1, OV/BV=1, p=8.

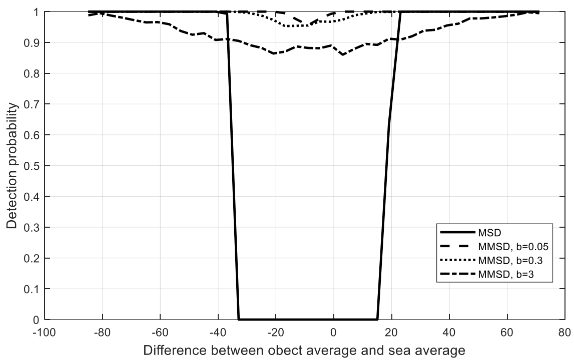

Fig.9. Detection probability vs difference between object average and sea average, NBR=0.1, OV/BV=4, p=8.

Figs.4 and 5 show an example of an object model and an example of a real object (the part of the Fig.3). Comparing these images shows some difference between the model and the real image, but their averages and standard deviations are the same. We have experimentally evaluated the MSD and MMSD performance in the presence of the artificial object on the real sea surface (the distance about 200 m). The dimensions of the object were 10x20 pixels, the average power of the reflections and the standard deviation changed during the experiments. Additive channel noise with a given intensity has been added to all images. The detectors analyze 300 pixels (10x20) at each frame and, for each frame, make a decision on the presence or absence of an object by comparing the result of processing 300 pixels (one number is formed) with a threshold. If the threshold is exceeded, a decision is made on the presence of an object in the 10x20 section. To implement the detection, we first selected a section of the sea image without an object, in which the detections were carried out in order to establish a threshold providing a false alarm probability of 0.01. In the selected area, the detection process was implemented 1000 times in 1000 frames. The output values of the detectors (1000 numbers) were analyzed and ordered in ascending order, and a threshold equal to the tenth of the maximum was assigned. Obviously, it is difficult to implement high-quality detection of an object with statistical parameters identical to the sea with detectors synthesized using statistical methods. Therefore, in this paper, the dependence of the detection probability on the difference between the mean values of the sea and the object was investigated for various ratios between the standard deviations of the object and the sea. The ratio of the channel noise power to the sea power also changed. All experiments and calculations were performed for a false alarm probability of 0.01.

Figs. 6 shows the results of experiments, where NBR is the ratio of the power of the channel noise to the power of reflections from the sea, OV/BV is the ratio of the dispersion of the object to the dispersion of the sea, p is the maximum frequency of the object, and b is the sensitivity coefficient of the MMSD. The graphs show that the minimum detection probability corresponds to the minimum of the difference between the averages object and the sea for both MSD and MMSD. Note that the standard deviations of the reflections from the object and the sea are the same. In this case, only MMSD provides high-quality detection at an appropriate value of the sensitivity coefficient b. This is explained by the presence of the second term in the MMSD algorithm, which calculates the logarithm of the ratio of the power of reflections from an object to the power of reflections from the sea in the subspace $\langle \boldsymbol{H}_S^{\perp} \rangle$ of sufficiently high frequencies. In practice, the surface of objects has a quasi-uniformly distributed intensity of reflections and therefore their spectrum is concentrated around zero frequencies. The sea surface has a significant irregularity in the intensities of the reflections. The reflections from the agitated sea have intense higher frequency components (Figs.1, 2). To compare the detection quality versus the spectral width of the object p, Fig.7. Analysis of the curves shows that with a decrease in the value of p, the quality of detection increases. In the paper, the influence of channel noise was assessed. In Fig. 8 the value OV/BV=0.1 and it is many times higher than this ratio for Figs. 6 and 7. Comparison shows that an increase in channel noise significantly degrades the quality of detection. Under conditions of intense channel noise, the detection quality is improved if the object has a higher dispersion than reflections from the sea (OV/BV=4)]. This is shown in Fig.9.

V. CONCLUSION

1. MMSD allows detecting low-contrast floating objects.
2. In the case of a high-contrast object, the first term of the algorithm (5) ensures high detection quality. The second term in (5) is sensitive to the difference at relatively high frequencies of the energy from the sea and from the object.
3. To implement detection using MMSD, an experimental estimate of the spectral width of a floating object is required.
4. The assessment of the quality of detection of MSD and MMSD carried out in this work using real images of the sea surface confirms the results obtained on the basis of the model of reflections from the sea surface as a Gaussian process [10].

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