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OBJECTS DETECTION BASED ON THE SEA SURFACE VIDEO FRAGMENTS CROSS-CORRELATION

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Abstract
The work is devoted to the development of a method for the objects detecting on an agitated sea surface video based on the analysis of the differences in the variability of the object and the sea surface image fragments on the neighboring frames. The proposed method does not use data about the object size, its shape, brightness, etc. The decision function has been developed that can be used to estimate the variability of a given frames fragment, based on the normalized cross-correlation coefficients values of the corresponding fragments on a video subsequent frames. The decision rule has been developed based on the proposed decision function, in which we use the threshold value (the critical domain boundary) determined at the training stage when analyzing the frames sequence fragments containing only the agitated sea surface image. The efficiency of the developed objects detection method on the agitated sea surface is demonstrated based on computational experiments. The values of the decision function critical domain boundary obtained at the training stage and the corresponding values of the type II error probability at the detection stage are given. The presented computational experiments results demonstrate that the developed method makes it possible to detect the object on video frames with the type II error probability equal to zero.

Keywords: object detection; video recording; agitated sea surface; sequential frames; image fragment distortion; normalized cross-correlation coefficient
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ОБНАРУЖЕНИЕ ОБЪЕКТОВ НА ОСНОВЕ ВЗАИМНОЙ КОРРЕЛЯЦИИ ФРАГМЕНТОВ ВИДЕО КАДРОВ МОРСКОЙ ПОВЕРХНОСТИ

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Аннотация
Работа посвящена разработке метода обнаружения объектов на видеозаписи взволнованной морской поверхности на основе анализа различий в изменчивости изображений объекта и фрагментов изображения морской поверхности на соседних кадрах. В предложенном методе не используются данные о размерах объекта, его форме, яркости и др. Разработана решающая функция, которая может быть использована для оценивания изменчивости заданного фрагмента кадра на последующих кадрах видео, на основе значений нормированных коэффициентов взаимной корреляции соответствующих фрагментов. Разработано решающее правило на основе предложенной решающей функции, в котором применяется пороговое значение (граница критической области), определяемое на этапе обучения при анализе фрагментов последовательности кадров, содержащих только изображение взволнованной морской поверхности. Продемонстрирована работоспособность разработанного метода обнаружения объектов на взволнованной морской поверхности на основе вычислительных экспериментов.

Приведены значения границы критической области решающей функции, полученные на этапе обучения, и соответствующие значения вероятности ошибки 2-го рода на этапе обнаружения. Приведенные результаты вычислительных экспериментов демонстрируют, что разработанный метод позволяет обнаружить изображение объекта на кадрах видеозаписи при вероятности ошибки 2-го рода равной нулю.
Ключевые слова: обнаружение объектов; видеозапись; взволнованная морская поверхность; последовательные кадры; искажение фрагмента изображения; нормированный коэффициент взаимной корреляции
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1. INTRODUCTION

The tasks of detecting various objects in the video frames arise during the development of surveillance, control and management systems in the human activity various fields. For example, the solution of detection tasks is required when creating machine vision systems in industrial production to control production processes, in the transport sector - to monitor the traffic situation, in the field of monitoring the individual territories - to monitor the current situation, in medicine - to analyze the results of surveys, etc. Various fields of the surveillance systems application require the development of various methods for detecting objects in images and video recordings frames, taking into account the detecting objects specific properties, as well as the features of their environment (background).

Methods based on the optical flow calculations [1, 2], as well as the use of the Kalman filter [3] are widely used to detect moving objects. The methods given in [4-6] allow objects to be detected based on the calculation of various similarity measures of the analyzed images fragments. The entropy-based method [7], the method of clustering wavelet coefficients [8], the maximal reference cell approach [9], the detection method for the hyperspectral images [10], the Reed, Mallett and Brennan algorithms [11], the detection method in clutter [12], as well as methods based on the detection and analysis of key, special features in which the variety of detectors and descriptors are used [13] are also used to detect objects. A significant group of detection methods is based on the use of the various types neural networks, for example, [14].

One of the rather difficult tasks of detection on video frames is the objects detection on an agitated sea surface, which is due to the complex structure of the sea surface images on a separate frame, to the significant variability of the sea surface images on neighboring frames, as well as possible movements and distortions of the observed objects. To solve these tasks if there is information about changes in the pixels brightness of the objects and background images, methods based on matched subspace detectors [15, 16] and their various modifications are used [17-19]. A method for detecting small objects floating on an agitated sea surface is given in [20].

It should be noted that one of the significant drawbacks of many known detection methods is the requirement for a priori information about various properties of the object and the background, which are quite difficult to obtain when solving the problem of detecting objects on an agitated sea surface.
The paper proposes a method for detecting objects on an agitated sea surface, which does not require a priori information about the shape, size and other characteristics of the desired objects.

2. THE METHOD

The method for the objects detecting on the agitated sea surface video developed in the work is based on the practical observations results showing that in most cases the object image changes slightly on video neighboring frames, unlike the sea surface video frames containing an images of the different lengths and different propagation directions waves. At the same time, the developed method does not require information about the objects size, shape, their pixels brightness changes frequency on a frames sequence, etc.

Initially, to solve the objects detection problem on the agitated sea surface video frames, we formulate the main hypothesis H_0: the object image is present in the given frame fragment. Checking the fulfillment of this hypothesis allows you to split the frame fragments into two classes: containing the object image and all the others. It is proposed to use the corresponding fragments cross-correlation coefficients values as the features that allow us to estimate the separate frame fragment belonging to one of these classes.

To test the main hypothesis validity, we developed the following decision function, which is a given fragment variability estimate on the video subsequent frames. This decision function is based on the normalized cross-correlation coefficients analysis for a given frame fragment with the images on subsequent video frames.

To test the above hypothesis validity, we develop the following decision function, which is an estimate of the given fragment variability on subsequent frames of the video. This decision function is based on the normalized cross-correlation coefficients analysis of the given fragment image on the frame with the images on subsequent video frames.

Consider a sequence $S=(S_k)$, $k=1,2,...,K$, containing K subsequent video frames with $N_1 \times N_2$ pixel dimensions. On the first frame S_1 of the sequence S we will set a fragment $F=(f_{i_1 i_2})$, $i_1=1,2,...,M_1$, $i_2=1,2,...,M_2$, with $M_1 \times M_2$ pixel dimensions:

$$N_1 > M_1, \quad N_2 > M_2. \tag{1}$$

For each next frame S_k, $k=2,3,...,K$, we calculate the maximum normalized cross-correlation coefficients values σ_k of this frame S_k and a given fragment F based on the following ratio [21-23]:

$$\sigma_k = \max_{j_1,j_2} \frac{\sum_{i=1}^{M_1}\sum_{j=1}^{M_2}(s_{k,i+j_1-1,j+j_2-1}-a_{k,j_1j_2})(f_{ij}-a_F)}{\sqrt{\sum_{i=1}^{M_1}\sum_{j=1}^{M_2}(s_{k,i+j_1-1,j+j_2-1}-a_{k,j_1j_2})^2\sum_{i=1}^{M_1}\sum_{j=1}^{M_2}(f_{ij}-a_F)^2}}, \tag{2}$$

$$j_1=1,2,...,N_1-M_1+1, \quad j_2=1,2,...,N_2-M_2+1,$$
$$k=2,3,...,K,$$

where $S_k=(s_{k,ij})$ – the frame S_k, $k=2,3,...,K$, with $N_1 \times N_2$ pixel dimensions,

a_{k,j_1j_2} – the average pixel value of the frame fragment S_k, corresponding to different values j_1 and j_2, $j_1=1,2,...,N_1-M_1+1$, $j_2=1,2,...,N_2-M_2+1$,

$$a_{k,j_1j_2}=\frac{1}{M_1M_2}\sum_{i=1}^{M_1}\sum_{j=1}^{M_2}s_{k,i+j_1-1,j+j_2-1}, \tag{3}$$

$F=(f_{ij})$ – the frame fragment F with $M_1 \times M_2$ pixel dimensions, corresponding to a given frame fragment S_1,

a_F – the average value of frame fragment F pixels:

$$a_F=\frac{1}{M_1M_2}\sum_{i=1}^{M_1}\sum_{j=1}^{M_2}f_{ij}. \tag{4}$$

The coefficients (2) values change in the interval $[-1,1]$.

The decision function has the form:

$$W(F)=\sum_{k=2}^{K}\sigma_k\theta(\sigma_k-T_\sigma), \tag{5}$$

where $\theta(\sigma_k-T_\sigma)$ – the Heaviside function [24] having the next form:

$$\theta(\sigma_k - T_\sigma) = \begin{cases} 1, & \sigma_k \ge T_\sigma, \\ 0, & \sigma_k < T_\sigma. \end{cases} \tag{6}$$

T_σ – a threshold value that characterizes the sea surface images variability, for example,

$$T_\sigma = 0.85\,. \tag{7}$$

The threshold T_σ changing allows you to change the developed method sensitivity when analyzing of the sea surface images with the different degree of sea agitation.

The decisive rule which allow you to form the decision function $W(F)$ (5) critical domain, is proposed in the following form:

$$\sum_{k=2}^{K} \sigma_k \theta(\sigma_k - T_\sigma) < T_W\,, \tag{8}$$

where T_W – where is the threshold value (the critical domain boundary), which value is determined at the training stage when analyzing the frames sequence fragments that do not contain an object image, for example, $T_W = 0.91$.

Thus, we have that the interval $[0, T_W[$ is the decision function $W(F)$ (5) critical domain in which the main hypothesis H_0 is rejected; the interval $[\,T_W, 1]$ is the decision function $W(F)$ values domain when the main hypothesis (a given fragment contains an object image) is accepted.

At the training stage, it is proposed to choose the decision function $W(\tilde{F})$ (5) maximum value as a threshold value T_W, obtained by analyzing fragments $\tilde{F}$ that do not contain an object image and are located in a given training area L on a frames sequence,

$$T_W = \max_{\tilde{F} \subset L} W(\tilde{F})\,. \tag{9}$$

To reduce the false selections amount of the sea surface fragments as containing an object image, it is proposed to use the following modified threshold value T_W:

$$T_W = \max_{\tilde{F} \subset L} W(\tilde{F})(1+\varepsilon)\,, \tag{10}$$

where ε – a small positive number, for example,

$$\varepsilon = 0.01\,. \tag{11}$$

3. THE COMPUTATIONAL EXPERIMENTS

The computational experiments were carried out to evaluate the developed method operability for selecting the frames fragments containing an object image. The study was carried out at different values of the fragment dimension, the threshold value T_σ (7) which characterize the sea surface images variability, as well as at different amount K of analyzed sequential frames (the frames amount in the block).

For conducting the computational experiments we selected the Video1, obtained from open Internet sources, which first frame is shown in Figure 1. The Video1 contains images of a fairly fast moving boat on a relatively calm sea surface.

Figure 1 shows the learning and detection areas marked in the first frame of the Video 1.

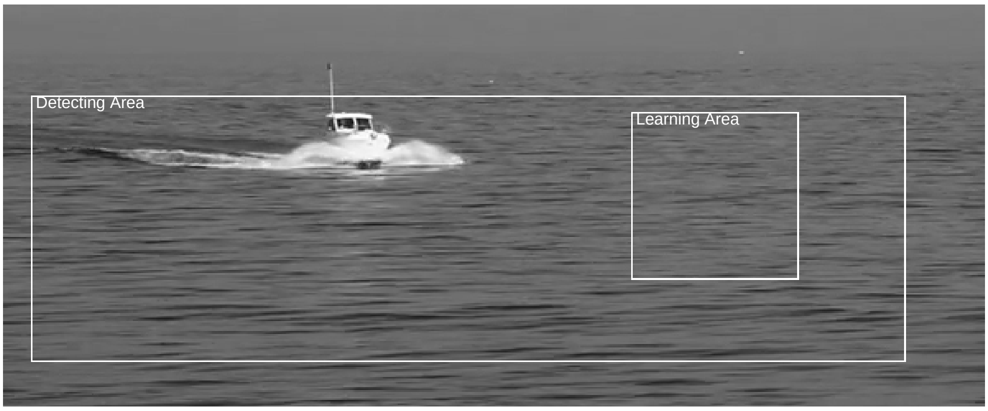

Fig. 1. The learning and detection areas (the first frame of the Video 1)
Рис. 1. Области обучения и обнаружения (первый кадр Video1)

Table 1 shows the critical domain boundary values T_W (threshold value) obtained at the training stage when analyzing fragments of the Video1 frames in the training area shown in Figure 1, with the various developed method parameters: such as the frames amount K in the block, the analyzed fragments dimension $M_1 = M_2$ and the threshold value T_σ (7).

Table 1

The critical domain boundary T_W, the Video1 frames

Таблица 1

Граница T_W критической области, кадры видео Video1

M_1 \ T_σ	0.7	0.75	0.8	0.85	0.9	0.95
The frames amount in the block, $K = 5$						
5	0.9954	0.9954	0.9954	0.9954	0.9954	0.9954
10	0.9714	0.9714	0.9714	0.9714	0.9714	0.9714
15	0.9411	0.9411	0.9411	0.9411	0.9411	0.4835
20	0.9236	0.9236	0.9236	0.9236	0.7061	0.2462
The frames amount in the block, $K = 10$						
5	0.9863	0.9863	0.9863	0.9863	0.9863	0.9863
10	0.9153	0.9153	0.9153	0.9153	0.7175	0.4317
15	0.8913	0.8913	0.8913	0.6133	0.5188	0.2149
20	0.8347	0.7548	0.5809	0.4105	0.3138	0.1094
The frames amount in the block, $K = 15$						
5	0.9701	0.9701	0.9701	0.9701	0.9701	0.9014
10	0.8944	0.8944	0.8383	0.7779	0.4612	0.2776
15	0.6746	0.5730	0.5730	0.3943	0.3335	0.1381
20	0.6951	0.5390	0.3734	0.2639	0.2017	0.0703

In Table 1, the critical domain boundary values T_W are marked in gray, which do not change when the threshold value T_σ decreases (7).

To estimate the developed method operability, it is advisable to use the type II error probability when the sea surface fragment is selected as an object image and not to estimate the type I error probability when a separate fragment containing an object image is not selected), since for solving the problem considering in this paper there is no need to identify the location of all object fragments, but it is sufficient to indicate the presence of the separate object fragments on the frame.

The type II error probability is calculated based on the following ratio:

$$P_2 = \frac{N_{fd}}{N_s}, \tag{12}$$

where N_{fd} – is the selected fragments amount that do not contain an object image (falsely selected), N_s – is the fragments amount in the detection area that do not contain an object image (fragments of the sea surface).

Table 2 shows the type II error probability values obtained at the detection stage when analyzing the Video1 frames fragments in the detection area shown in Figure 1, in accordance with the developed method parameters values given in Table 1. When conducting these computational experiments the ε value (11) was chosen to be 0.01 to modify the critical domain boundary value (10).

Table 2 does not contain the values corresponding to the developed method parameters given in Table 1, with which the fragments containing the object images were not selected. This result is caused, first of all, by the critical domain boundary value being close to unity values (see Table 1), which were obtained as a result of the presence in the training area of the small sea surface fragments that practically do not change from frame to frame.

Table 2

The type II error probability ($\varepsilon = 0.01$), the Video1 frames

Таблица 2

Вероятность ошибки 2-го рода ($\varepsilon = 0,01$), кадры видео Video1

M_1 \ T_σ	0.7	0.75	0.8	0.85	0.9	0.95
The frames amount in the block, $K = 5$						
10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
15	0.0330	0.0330	0.0330	0.0330	0.0302	0.0440
20	0.0316	0.0316	0.0316	0.0316	0.0316	0.0474
The frames amount in the block, $K = 10$						
10	0.0207	0.0207	0.0207	0.0181	0.0155	0.0078
15	0.0165	0.0165	0.0165	0.0275	0.0137	0.0440
20	0.0053	0.0158	0.0211	0.0526	0.0316	0.0474
The frames amount in the block, $K = 15$						
5	0.0032	0.0032	0.0032	0.0032	0.0032	0.0063
10	0.0155	0.0142	0.0310	0.0181	0.0259	0.0103
15	0.0934	0.0824	0.0330	0.0357	0.0137	0.0440
20	0.0105	0.0105	0.0263	0.0526	0.0316	0.0474

It should be noted, analyzing the data given in Table 2, that with the fragments dimension $M_1 = 10$ and the frames amount in the block $K = 5$, the developed method made it possible to detect the object fragments with the type II error probability $P_2 = 0$. The remaining values of the type II error probability in Table 2 correspond to a certain amount of correctly selected fragments.

Table 3 shows the type II error probability values obtained at the detection stage when analyzing the Video1 frames fragments in the detection area shown in Figure 1, in accordance with the developed method parameters values given in Table 1. When conducting these computational experiments the ε value (11) was chosen to be 0.05 to modify the critical domain boundary value (10). Table 3 does not contain the values corresponding to the developed method parameters given in Table 1, with which the fragments containing the object images were not selected.

Table 3

The type II error probability ($\varepsilon = 0.05$), the Video1 frames

Таблица 3

Вероятность ошибки 2-го рода ($\varepsilon = 0,05$), кадры видео Video1

M_1 \ T_σ	0.7	0.75	0.8	0.85	0.9	0.95
The frames amount in the block, $K = 5$						
15	0.0000	0.0000	0.0000	0.0000	0.0000	0.0192
20	0.0000	0.0000	0.0000	0.0000	0.0211	0.0474
The frames amount in the block, $K = 10$						
10	0.0000	0.0000	0.0000	0.0000	0.0103	0.0078
15	0.0027	0.0027	0.0027	0.0247	0.0027	0.0192
20	0.0000	0.0053	0.0105	0.0368	0.0211	0.0474
The frames amount in the block, $K = 15$						
10	0.0000	0.0000	0.0194	0.0142	0.0246	0.0103
15	0.0797	0.0687	0.0302	0.0330	0.0027	0.0192
20	0.0105	0.0105	0.0105	0.0368	0.0211	0.0474

Note that all the type II error probability values, given in Table 3, are obtained in the presence of correctly selected object fragments.

Thus, the data given in Tables 1 and 2 demonstrate that the developed method makes it possible to select frame fragments containing the object image with the type II error probability $P_2 = 0$.

It is assumed that when analyzing videos containing an image of a more agitated sea surface than on Video1, the type II error probability will be zero or have lower values than in Tables 2 and 3, with various parameters of the developed method.

As an example of detecting the object fragments with the type II error probability $P_2 = 0$, the Figure 2 shows in white the fragments which are classified as fragments containing an object image based on the developed method with the following parameters:

- frames amount in a block, $K = 10$,
- dimension of the analyzed fragments, $M_1 = M_2 = 10$ pixel,
- threshold value characterizing the variability of sea surface images, $T_\sigma = 0.85$,
- the ε value (11) used to modify the critical domain boundary value (10), $\varepsilon = 0.05$.

Fig. 2. Fragments selected as containing an object image, when $K = 10$, $M_1 = M_2 = 10$, $T_\sigma = 0.85$, $\varepsilon = 0.05$

Рис. 2. Фрагменты, выделенные как содержащие изображение объекта, при $K = 10$, $M_1 = M_2 = 10$, $T_\sigma = 0.85$, $\varepsilon = 0.05$

Figure 2 shows that the fragments containing the image of the boat swirl are attributed to the object. Since these fragments characterize the presence of an object in the image, it can be assumed that with the specified parameters of the method in Figure 2, only fragments containing the object image are selected.

Thus, the results of computational experiments show that the developed method for detecting the objects on the agitated sea surface allows to select fragments containing object images, and the developed method does not allow false selection of fragments that do not contain an object with certain values of the method parameters.

CONCLUSIONS

The method for the objects detecting on an agitated sea surface video based on the observation that in neighboring video frames the object image often changes less compared to fragments of the sea surface image is proposed in this work. In the proposed method, to detect an object, data about the object size, its shape, changes in its brightness on frames, etc. are not required.

The main hypothesis is formulated in the paper: the object image is present in a given frame fragment, to verify the implementation of which the set of the frame fragments is divided into two classes based on the analysis of the features values obtained as a result of calculating the cross-correlation coefficients values of the corresponding fragments on the video subsequent frames. A corresponding decision function has been developed that can be used to estimate the variability of a given fragment on the subsequent video frames.

A decision rule has been developed based on the proposed decision function, in which a threshold value (the critical domain boundary) is applied, determined at the training stage when analyzing the frames sequence fragments containing only the agitated sea surface image.

The efficiency of the developed objects detection method on the agitated sea surface is demonstrated based on computational experiments. The analyzed video contains images of a fairly fast moving boat on a relatively calm sea surface. Computational experiments were carried out at various values of the developed method parameters. The values of the decision function critical domain boundary obtained at the training stage and the corresponding values of the type II error probability at the detection stage are given. The type I error probability were not evaluated in the work, since in the problem under consideration it is sufficient to detect several separate object fragments on an agitated sea surface video frame. The presented computational experiments results demonstrate that the developed method makes it possible to detect the object on video frames with the type II error probability equal to zero.

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