Based on Bagging Method Moving Object Detection Design

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***Abstract*— Focusing on the disturbance of moving cast shadow, a Bagging moving cast shadow removal method is proposed. Collecting shadow discrimination features from multiple shadow discrimination models, a shadow detector is trained by employing Bagging ensemble based learning framework. The shadow detector can automatically select effective shadow discrimination features and be updated online adaptively. Experimental results demonstrate the effectiveness of the proposed method.**

***Keywords*-moving object; features; shadow; Bagging; detection**

I. INTRODUCTION

Motion shadow is due to the moving target hides some or all of the light and shadows on the background. Motion shadow interference is an important factor to affect the moving target detection, because of the shadow and the target and the background difference is very big, and they often have the same movement, shadows are often made by differentiating for moving targets. The shadow of moving object segmentation and extraction: target combined, that is, two or more goals because the shadow and connected into a connected domain, was convicted of a subsequent target extraction algorithm goal; Target appearance changes, the impact to accurately extract the target will be very bad shape information of application; The disappearance of the target, often occur in a target shadow casting on another goal. In order to eliminate the interference of the motion shadow, there is a lot of shadow detection algorithm.

These algorithms can be divided into the following three: (1) the method based on geometric model, using the camera position, the scene geometric constraints between the surface geometric characteristics and objective to detect the shadow, need to assume and prior knowledge. (2) the method based on color model, in RGB, HSV and YUV space using a variety of threshold segmentation foreground and background, shadow, etc., using statistical models to describe shadow pixel color values. (3) detection method based on texture model, using cast shadows to reduce the corresponding background pixel gray value, do not change the characteristics of the pixel neighborhood texture shadow detection[1,2].

The above methods need to experience a threshold, the threshold once set, with image segmentation results of content of different and different, scene adaptability is not strong. In addition, the selection of features is too single limits the detection performance of the play. This paper proposes a motion shadow elimination based on Bagging ensemble learning method, this method adopts multiple shadow identification model for the shadow identification characteristics, using selective integration framework of Bagging training shadow detector, can to shadow detector adaptive online updates.

II. BAGGING INTEGRATION ALGORITHM

There are a lot of current integration algorithm, these algorithms can be roughly divided into serial algorithm and parallel algorithm for generating two categories, the typical algorithms are respectively Bagging and Boosting algorithms. Bagging algorithm through the study of the several times of the training sample set is back on the random sampling, usually get a sampling and sample subset of the training sample set of the same size, the use of the individual classifiers subset training[3].

Although the starting point is the integration algorithm depends on using multiple learning to improve the generalization performance of the overall learning, but learning is not the more the better. Experiment found that part of the individual learning from existing learning device for integration, can obtain better generalization performance. In order to give attention to two or more things Bagging algorithm of noise resistance, while keeping the learning performance of Boosting algorithm, using selective integrated the advantages of improved learning algorithm generalization ability. In this paper, the selective integration algorithm based on Bagging generated shadow detector, the algorithm using the Bagging method to generate multiple individual learning, by Boosting method for selective integration.

III. SHADOW IDENTIFICATION MODEL

Shadows are due to the light source is blocked by the object, a pixel values I expressed in the following model:

$$I = E \cdot \rho \tag{1}$$

The light is E, the object surface reflectivity is ρ. Hypothesis is parallel light from the light source, light further approximation

$$E=\begin{cases} E_1+E_2\cos\theta & \text{no barrier} \\ E_1+kE_2\cos\theta & \text{half barrier} \\ E_1 & \text{full barrier} \end{cases} \quad (2)$$

Light environment E_1, the main light source illumination E_2, k ($0<k<1$) determine the parameters of half shade degree value, θ direction of the light source and surface normal direction angle. Half a block is tend to produce thin, translucent shades; all condition can produce the black shadow[4].

Gradient Shading Model

For each pixel point $p(x,y)$, define the direction of the horizontal and vertical gradient, respectively

$$dx=\left|f(x+1,y)-f(x,y)\right| \quad (3)$$

$$dy=\left|f(x,y+1)-f(x,y)\right| \quad (4)$$

The grey value is $f(x,y)$. Then gradient intensity and gradient direction are

$$g=\sqrt{dx^2+dy^2} \quad \varphi=\arctan\frac{dy}{dx} \text{ respectively} \quad (5)$$

When background pixel is covered by the shadow, the gradient intensity and gradient direction basically remain unchanged. When it is covered by moving target, it will produce bigger change. Therefore, the calculation of foreground and background pixel gradient intensity and direction change, distinguish shadows or goals, meet the type for the shadow

$$M=\left|g_c-g_b\right|\approx 0;\quad \theta=\left|\varphi_c-\varphi_b\right|\approx 0 \quad (6)$$

The foreground and background gradient intensity g_c, g_b, foreground and background gradient direction φ_c, φ_b respectively[5].

Texture Shadows Model

Shadow projected on the background while decreases the intensity of the background image, background image texture features basic don't change. As a result, the texture is also commonly used shadow detection model, texture shadows model affected by the brightness is very small [6,7].

In this paper, using the center pixel texture model is established with neighborhood pixel ratio, defined as follows:

$$R(x,y)=\frac{f(x,y)}{f(i,j)} \qquad (i,j)\in\Theta(x,y)$$

$$\Theta(x,y)=\{(i,j)\,|\,0<(i-x)^2+(j-y)^2\le r^2\} \quad (7)$$

The image coordinates (x,y) of pixels neighborhood pixel coordinates collection, neighborhood pixel number N.

Assuming that the image and the center pixel neighborhood pixels have approximately the same light., available

$$\frac{f(x,y)}{f(i,j)}=\frac{E\cdot\rho_c}{E\cdot\rho_n}=\frac{\rho_c}{\rho_n} \quad (8)$$

Light energy is E. Pixels (x,y) and (i,j) reflectivity are ρ_c、ρ_n. The same background corresponds pixels in the image

$$\frac{f_b(x,y)}{f_b(i,j)}=\frac{E'\cdot\rho_c'}{E'\cdot\rho_n'}=\frac{\rho_c'}{\rho_n'} \quad (9)$$

Namely:

$$R_{dif}(x,y)=\sum_{(i,j):f(i,j)\in\Theta(x,y)}\left(\frac{f(x,y)}{f(i,j)}-\frac{f_b(x,y)}{f_b(i,j)}\right)^2\approx 0 \quad (10)$$

Shadow Elimination Algorithm

The training sample $\{x_i,y_i\}_{i=1}^N$, shadows identify characteristic vector x_i, category labels $y_i\in\{1,-1\}$, shadow $y_i=1$, goals $y_i=-1$. Using the classification of the least-squares regression plane as an individual classifier:

$$H(x):H(x)=\operatorname{sgn}(h^T x) \quad (11)$$

$$h=(A^T W^T W A)^{-1} A^T W^T W y \quad (12)$$

Samples of augmented matrix is A, the diagonal matrix is W. In order to avoid a number of positive and negative cases samples don't equal, cause the deviation of classifier. Set positive samples N, negative cases of samples M.

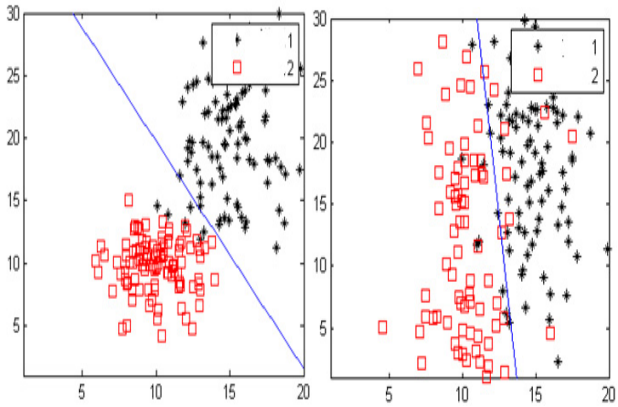


Figure 1. classification results of one individual classifier

Because the shadow identification features using adaptive selection mechanism, when generating the individual learning, using the random selection of training samples in the training sample set, also need to random

characteristics of the combination of a kind of combination to build the corresponding sample feature vector[8].

The steps of shadow removal method are as follows:

Step 1: manually tag from the sequence of the first frame part of the target and shadow pixel samples.

Step 2: All the pixels was sentenced for target, determine its relationship with corresponding pixel gray in the background. If is satisfied $g_c > g_b$, it is the target point.

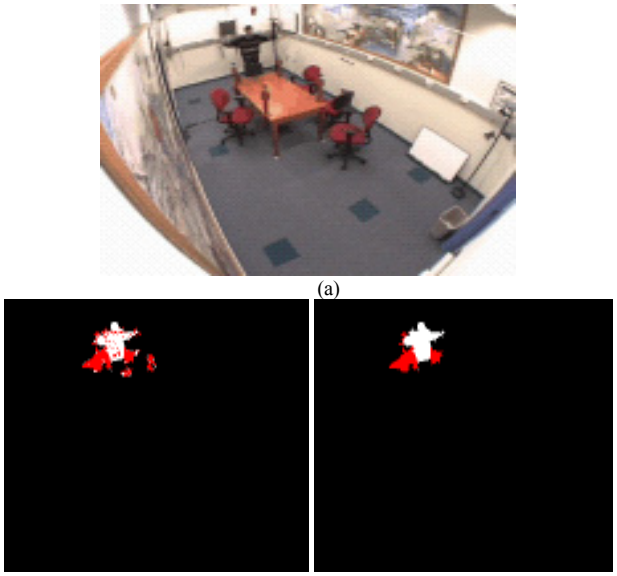
Step 3: the reprocessing of detection results

Step 4: online update integrated classifier

As the scene illumination change, shadow characteristics change, target and shadows are obtained by the new samples for integrated classifier online updates.

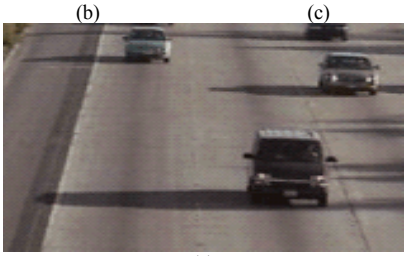
IV. THE EXPERIMENTAL RESULTS AND ANALYSIS

In this paper, the shadow detection algorithm takes shadow detection sequence in the Intelligent Room, Laboratory, Highway I. Figure in each row from left to right in turn to the original test results, the post-processing and processing test results. Test results were the target of the white, shadow of red.

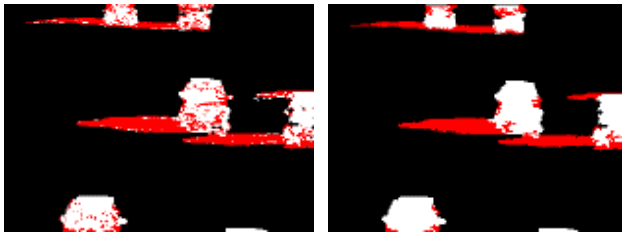


(a)

(b) (c)



(a)



(b) (c)

Figure 2. Detection results of proposed method.
(a) original image;(b)detection results without post-processing;(c)detection results with post-processing

In addition, it compares the proposed algorithm and two typical shadow detection methods, the GMM/GMSM algorithm based on color feature and the Ratio-Edge algorithm based on texture feature[9,10]. In figure 3, the first listed as the original image, the second and third columns of the GMM/GMSM algorithm, the Ratio-Edge algorithm and the paper algorithm. Test results were the target of the white, shadow of red.

This algorithm used the multiple features of avoiding uncertainty, the choice of the threshold for shadow prospects classifier online update, improve the algorithm is adaptive to the scene changes.

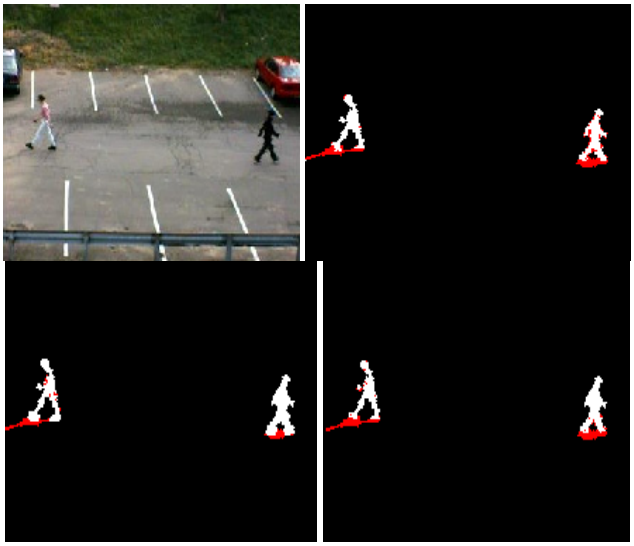


Figure 3. detection results of proposed method, GMM/GMSM method and Ratio-Edge method

V. CONCLUSION

For moving shadow interference, this paper proposes a shadow elimination method based on the integration of Bagging algorithm. This method takes advantage of the selectivity of Bagging integration algorithm improve the learning performance, suppress interference noise samples. Combined with the feature of multiple shadow identification model for the shadow collection, in learning within the framework of adaptive selection of the most effective shadow identification features, use online samples to update a classifier. The simulation results show that the superiority of the proposed algorithm in this paper.

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