Detecting Algorithm for Moving Objects Based on Bayesian Judging Criterion

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***Abstract*—This paper considers the problem of accuracy for judging threshold under the complicated circumstance. In the detecting system, threshold is one of the most important factor, it decides the accuracy of the detecting result. Because the circumstance is changing, the threshold is asked to adapt the change. The traditional algorithm can hardly satisfy the need of the system. Bayesian model is an efficient system based on statistics rule, and it can give a better detecting result. In order to adapt the change of the light in a same video sequence, Bayesian judging criterion is used to detect object, void warm price and falling report price is considered comprehensively, combined with likelihood function and Bayesian risk assessment, an adaptive threshold is obtained. The threshold is determined by mean and variance of the image, so it is an optimal threshold changed with every image. The optimal threshold is used to separate object from background. Compared with the traditional threshold, it can suit different circumstance. The experimental result shows that the background noise can be removed with the dynamic threshold and the moving object can be detected accurately.**

***Index Terms*—Bayesian criterion, object detecting, likelihood function, optimal threshold, statistics rule**

I. INTRODUCTION

Object detecting plays an important role in the smart surveillance system and pattern recognition. In surveillance system, object detecting is a key step and it decides the tracking result directly. If the fixed threshold is selected to detect the object, we know, the algorithm is simple and the system is real time. But, the circumstance is complex and the object is moving, the fixed threshold can’t adapt the change of all the circumstances. So, more and more detecting algorithm is proposed[1]-[10]. In order to satisfy the different environment, the detecting algorithm gets more and more complicated[11]-[18], and the real time system can be assured hardly. So, a fast, exact and efficient detecting algorithm is still a challenging topic. In paper[19], A new temporal based target detection algorithm was presented by using static background elimination to deal with the drawback of large scale data processing, and real-time implementation in temporal filtering, the parameter of the model was estimated by introducing least square method and using the new model, static background pixels could be eliminated. The method could have higher speed and computational efficiency. An adaptive approach to detect moving objects with a static camera was proposed in paper[20], the number of Gaussians for each pixel on-line was chosen, and the moving objects were detected by background subtraction. Paper[21] considers the problem of simultaneously detecting and tracking multiple targets. In the paper, the predominant challenge is to arrive at a computationally tractable approximation. A particle filtering scheme is developed for this purpose in which each particle is a hypothesis on the number of targets present and the states of those targets. The threshold measurement model presents a more challenging tracking environment than the non-threshold measurement model since a loss of information is incurred when threshold is performed. Preliminary results indicate that significantly improved results are obtained using non-threshold measurements. In paper[22], In order to make intelligent video surveillance system not only have a high accuracy rate but also be assured the real-time, a practical moving target detection and tracking algorithm was implemented using the method of Gaussian Mixture, and extracting foreground object using morphological operations. In order to overcome the limitation of Kernel-based mean shift (MS) tracker, a new method is proposed in paper[23], a robust object representation model from a large amount of data is built to realize tracking task. a support vector machine for training is adopt, The tracker is then implemented by maximizing the classification score. Experiments on localization and tracking show its efficiency and robustness.

In this paper, the limitation of the fixed threshold is considered. Made use of the void warm price and failing report price, combined with likelihood function and Bayesian criterion, a dynamic threshold which changed with the parameter of every image is given. The gray difference image is processed by the dynamic threshold

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to got a binary image only with object. The new threshold can suit the light change of the circumstance. This method can realize real-time tracking and make the object detection more accurately.

II. PREVIOUS WORKS FOR FIXED THRESHOLD

In the surveillance system with the steady surroundings, the fixed threshold can be used to detect the object. The process of the detecting is to obtain the difference image $D(i, j)$ with the object through background subtraction. Then, a suitable threshold is selected to separate the object from the background. The algorithm can be described as:

$$E(i, j) = \begin{cases} 1, & |D(i, j)| > T \\ 0, & otherwise \end{cases} \quad (1)$$

Here, $E(i, j)$ is the binary image with objects, sometimes, there are some noises in the binary image if the threshold is not suitable. i and j is the rank and row of a pixel, respectively. T is a threshold, and the experience value is changing between $10 \sim 30$. $D(i, j)$ is the gray difference image, $D(i, j) = F(i, j) - B(i, j)$, $F(i, j)$ is foreground image, $B(i, j)$ is background image.

We can see from formula (1) that in the difference image, the pixel which value is bigger than T is distinguished as object, and its value equals 1. The others are distinguished as noises and their value equal 0. So, a binary image with object only can be obtained. According to the binary image, the objects can be tracked and their behavior can be understood.

The different detecting result with different threshold is showed in figure1. Here (a) is the original image, (b) and (c) are detecting result with the threshold $T = 10$ and $T = 25$, respectively. We can conclude from the figure that if the threshold is small, the system can detect the object entirely, but the system causes more noise, showed in figure1 (b), so a perfect filter is asked to deal with the noise, the detecting algorithm will get more and more complex. On the other hand, if the threshold is too great, the noise can be controlled, but the detecting object is incomplete, showed in figure1 (c). In this case, the tracking will fail. So, a fixed threshold is difficult to satisfy the demand of detecting object accurately, because the circumstance is changing, the influence of the light is different in a same video sequence. A dynamic threshold is demanded to realize the accurate detecting task.

As we all know, the surroundings are changing with the weather and season, and those will cause light changing. A fixed threshold is difficult to satisfy the demand of detecting object accurately because the light is changing. Since the influence of the light is different in a same video sequence, if a tracking system uses a fixed threshold to detect the object, it is difficult to adapt all kinds of circumstance. Different influence will result in different noise, different threshold will need in order to detect object in a same video sequence. So, an adaptive threshold which changes with circumstance is demanded to finish the detecting task.

(a) (b) (c)

Figure 1. Different detecting result with different threshold
(a) The original image. (b) The detected result with the threshold $T = 10$. (c) The detected result with the threshold $T = 25$

III. BAYESIAN MODELING

The basic task of signal detection is to segment signal from noise. Bayesian judging criterion is an optimal judging criterion. Its task is to choose a suitable threshold in order to assure the average price is smallest. We call it Bayesian judge. The average price is expressed as $\overline{R}$, its mathematical expression is defined as[24]:

$$\begin{aligned} \overline{R} &= P(H_1)r_1 + P(H_2)r_2 \\ &= P(H_1)[P(D_0 / H_1)c_{00} + P(D_1 / H_1)c_{10}] \\ &+ P(H_2)[P(D_0 / H_2)c_{01} + P(D_1 / H_2)c_{11}] \end{aligned} \quad (2)$$

Here, r_1 is the conditional cost under the factor H_1 is true, r_2 is the conditional cost under the factor H_2 is true. In this paper, H_1 and H_2 are defined as:

H_1: Supposed that the signal is noise with mean m_1 and variance σ_1^2

H_2: Supposed that the signal is object with mean m_2 and variance σ_2^2

$p(H_1)$ and $p(H_2)$ are priority probability. c_{ij} is defined as the cost that hypothesis H_j is true but hypothesis H_i is chosen. Under the condition of double selection, the value of i and j is 0 or 1 only. Generally, c_{10} is defined to describe the cost that there is no signal but judging as signal, named void warm cost. c_{01} is defined as the cost that there is signal but judging as noise, named failing report cost. The value of c_{10} and c_{01} are presumed as 1 generally. c_{00} and c_{11} express the cost of the correct judgment and their values are 0.

Under the above hypothesis, r_1 and r_2 can be written as:

$$r_1 = P(D_0|H_1)c_{00} + P(D_1|H_1)c_{10}$$

$$r_2 = P(D_0|H_2)c_{01} + P(D_1|H_2)c_{11}$$

In this paper, there are only two types of signal in the image, so

$$P(D_0|H_1) = 1 - P(D_1|H_1)$$

$$P(D_0|H_2) = 1 - P(D_1|H_2)$$

So, we have

$$\overline{R} = P(H_2)c_{01} + P(H_1)c_{00} + P(H_1)(c_{10} - c_{00})$$
$$P(D_1/H_1) - P(H_2)(c_{01} - c_{11})P(D_1/H_2)$$

Obviously, void warm probability $P(D_1/H_1)$ and detecting probability $P(D_1/H_2)$ can be expressed as:

$$P(D_1/H_1) = \int_{D_1} p(x|H_1)dx$$

$$P(D_1/H_2) = \int_{D_1} p(x|H_2)dx$$

According to the definition, Bayesian judging criterion is to determine the judge region D_0, D_1 in order to make the average risk in formula (2) is minimum, the minimum risk is Bayesian risk.

The n dimension probability density function which called likelihood function is defined as $p(x/H_1) = p(x_1, x_2 \cdots, x_n / H_1)$ and $p(x/H_2) = p(x_1, x_2 \cdots, x_n / H_2)$ under the hypothesis H_1 and H_2, separately. So, the average risk can be expressed by likelihood function as following:

$$\overline{R} = P(H_2)c_{11} + P(H_1)c_{00} + \int_{D_1}\{P(H_1)(c_{10} - c_{00}) \quad (3)$$
$$p(x/H_1) - P(H_2)(c_{01} - c_{11})p(x/H_2)\}dx$$

The conditional probability density function is supposed as Gauss distribution. All of the hypothesis priority probability is presumed equality, and $c_{00} = c_{11} = 0$, $c_{01} = c_{10} = 1$. Then, Bayesian criterion can be replaced by maximum likelihood criterion. The hypothesis H_i will be chosen if $P(x/H_i)$ is maximum. The task of optimal judge is to decide which one is true in H_1 and H_2 according to input signal x. If the likelihood function of H_2 is greater than H_1, the signal will be judged as object. In this experiment, $n = 1$, so the likelihood function can be written as:

$$p(x/H_1) = \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{(x-m_1)^2}{2\sigma_1^2}} \quad (4)$$

$$p(x/H_2) = \frac{1}{\sqrt{2\pi}\sigma_2} e^{-\frac{(x-m_2)^2}{2\sigma_2^2}} \quad (5)$$

As we all know that the value on y direction of Gauss distribution function are all positive, when $x < 0$, $p(x/H_1) = p(x/H_2) = 0$.

Bayesian criterion asks that the selected region D_1 should satisfy:

$$P(H_2)(c_{01} - c_{11})p(x|H_2) \geq P(H_1)(c_{10} - c_{00})p(x|H_1)$$

After simplified calculation, we have:

$$\frac{p(x|H_2)}{p(x|H_1)} \geq \frac{P(H_1)(c_{10} - c_{00})}{P(H_2)(c_{01} - c_{11})}$$

According to the hypothesis above, the likelihood ratio can be obtained:

$$\Lambda(x) = \frac{p(x/H_2)}{p(x/H_1)} = \frac{\sigma_1}{\sigma_2} e^{-\frac{(x-m_2)^2}{2\sigma_2^2} + \frac{(x-m_1)^2}{2\sigma_1^2}} \quad (6)$$

So, the judge process changes into calculating the likelihood ratio of the input, then, compares with a threshold Λ_0, if $\Lambda(x) \geq \Lambda_0$, H_2 is true, otherwise, H_1 is true. Here, $\Lambda_0 = \frac{p(H_1)}{p(H_2)}$, the threshold is decided by the priority probability of the two hypothesis. The likelihood ratio can be showed in figure 2.

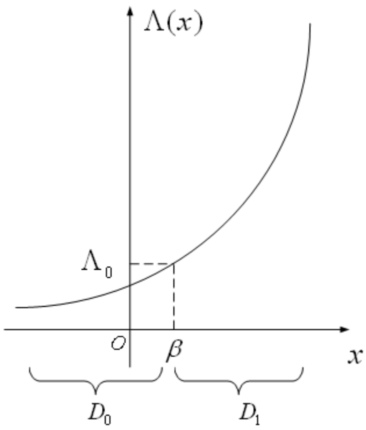

Figure2. Likelihood ratio and judging region

We can get the conclusion from figure2 that Bayesian judgment converts a comparison between detecting value and threshold β. If $x \geq \beta$, the region D_1 is judged as signal, otherwise, region D_0 is judged as no signal.

So, the goal of signal detecting is to separate the space into D_0 and D_1, select the signal according to threshold. Bayesian criterion can give an optimal estimation and make the risk is minimum.

In order to simplify the calculation, formula (6) can be written as:

$$\ln\Lambda(x) = \ln\frac{\sigma_1}{\sigma_2} - \frac{(x-m_2)^2}{2\sigma_2^2} + \frac{(x-m_1)^2}{2\sigma_1^{\ 2}} \qquad (7)$$

We let $\sigma_1^{\ 2} = k\sigma_2^{\ 2}$, here k is a constant. If $k \ge 1$, signal will be flooded by noise, so the object can be detected hardly. In this paper, the maximum noise variance equals signal variance, so, $k = 1$, and $\sigma_1^{\ 2} = \sigma_2^{\ 2} = \sigma^2$.

We can obtain the result from formula (7):

$$\ln\Lambda(x) = -\frac{x^2 - 2m_2x + m_2^2}{2\sigma^2} + \frac{x^2 - 2m_1x + m_1^2}{2\sigma^2}$$

$$= \frac{m_2 - m_1}{\sigma^2}x - \frac{m_2^2 - m_1^2}{2\sigma^2} \qquad (8)$$

Comparing formula (8) with the Log form of Λ_0, we can obtain the judging formula:

$$\frac{m_2 - m_1}{\sigma^2}x \underset{H_1}{\overset{H_2}{\gtrless}} \ln\Lambda_0 + \frac{m_2^2 - m_1^2}{2\sigma^2} \qquad (9)$$

Then

$$x \underset{H_1}{\overset{H_2}{\gtrless}} \frac{\sigma^2}{m_2 - m_1}\ln\Lambda_0 + \frac{m_2 + m_1}{2} \qquad (10)$$

The formula (10) can be rewritten as:

$$x \underset{H_1}{\overset{H_2}{\gtrless}} \beta \qquad (11)$$

Here, x is the detected pixel, β is the threshold and $\beta = \frac{\sigma^2}{m_2 - m_1}\ln\Lambda_0 + \frac{m_2 + m_1}{2}$. m_1 is mean of noise, m_2 is mean of object and σ^2 is variance of image. We can conclude from the formula (11), if $x > \beta$, H_2 is true and the pixel is object, if $x < \beta$, H_1 is true and the pixel is noise.

The process of signal detecting can be concluded in figure 3. The optimal detector is given in the figure base on Bayesian theory. Here, $\Lambda_0(x)$ is a nonlinear function about detecting value. Because the detecting algorithm is a nonlinear process, the all system is a nonlinear system. According to the input value of x, $\Lambda_0(x)$ can be calculated, Λ_0 is known, and an ideal detecting result can be obtained. An optimal judge system can be got according to the above calculation.

IV. OBJECT DETECTING

Background subtraction is one of the simple and effective method to detect object. Based on the traditional

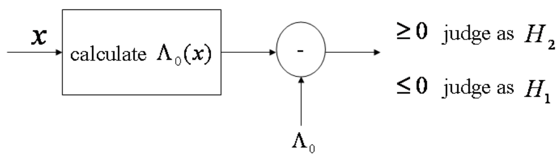

Figure3. The optimal detector based on Bayesian criterion

algorithm, the fixed threshold is improved. In order to obtain an adaptive threshold to detect the object, Bayesian theory is used to define the value under different circumstances. As we all know, mean m and variance σ^2 are very important parameters in signal processing, in this paper, under some reasonable hypothesis, a threshold based on mean and variance is obtained. This threshold is a dynamic value which is decided by the statistical parameter of every image. So, the optimal threshold can be calculated if m and variance σ^2 is known.

The object detection process with the new algorithm can be described in 3 steps as following:

(1) Obtain the gray difference image $D(i, j)$ with background subtraction. In this paper, background image is obtained through calculating mean and variance of 50 frames background in the video sequence. So, the system can ensure that the background alters with the circumstance. The above algorithm can be expressed as:

$$D(i,j) = F(i,j) - B(i,j)$$

Here, $F(i, j)$ is foreground image, $B(i, j)$ is background image.

(2) Calculate the optimal judging threshold β. In section Ш, the value of β has been discussed in detail. Its value can be written as:

$$\beta = \frac{\sigma^2}{m_2 - m_1}\ln\Lambda_0 + \frac{m_2 + m_1}{2}$$

Here, β is the optimal threshold which is determined by mean and variance to separate object from background. We can see from the formula, if the image is different, the value of β is different.

As we know that in a detected image, moving object is the interesting subject, background can be seem as noises. So, the priority probability of object and noises is same approximately, that is $\Lambda_0 = \frac{p(H_1)}{p(H_2)}$ =1. Under the hypothesis, β can be rewritten as:

$$\beta = \frac{\sigma^2}{m_2 - m_1}\ln\Lambda_0 + \frac{m_2 + m_1}{2} = \frac{m_2 + m_1}{2}$$

So, β is determined by the mean of background and foreground in fact. The reasonable hypothesis can simplify the calculating process, and realize a real time system.

(3) Obtain the binary image according to β, if a pixel value of the gray image is bigger than β, the pixel is object, otherwise, the pixel is noise.

$$E(i, j) = \begin{cases} 1, & |D(i, j)| > \beta \\ 0, & otherwise \end{cases}$$

Here, $E(i, j)$ is the detected result and $E(i, j)$ is a binary image, there are only two types of pixel in it, the value of object equals 1 and the value of noise equals 0. We can observe the object from it easily.

In figure 4, the experimental result is given under different circumstance to verify the feasibility of the new algorithm. (a) is foreground with objects and (b) is background. (c) is result after background subtraction, the gray difference image $D(i, j)$ is obtained. (d) is the detecting result with the new algorithm proposed in this paper.

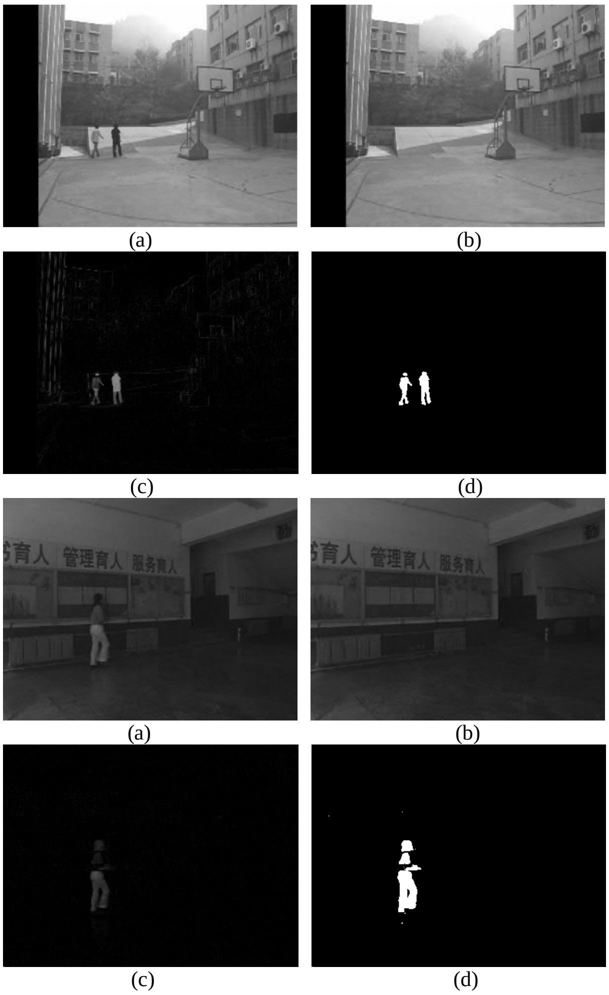

Figure4. Detecting result under different circumstance
(a) The foreground with objects. (b) The background. (c) The gray difference image. (d) The detecting result with the optimal threshold.

In the experiment, there are two objects under outdoors and one object under indoors. We can conclude from the result that there is no noise in the binary image and the detecting object is integrated, so β is an optimal threshold to detect the object accurately.

Ⅴ. EXPERIMENTAL RESULTS

We use 100 images in two video sequences under different indoor and outdoor circumstance with different number object to exam the accuracy of object detecting threshold. The detecting result is showed in table 1.

TABLE1
DETECTING ACCURACY FOR DIFFERENT THRESHOLD

threshold	Indoor circumstance		Outdoor circumstance	
	One object	Two objects	One object	Two objects
Fixed threshold	76.6%	68.8%	70.3%	63.5%
Optimal threshold	99.4%	98.7%	98%	96.9%

The data shows that the accuracy is better under indoor circumstance. If there is only one object in image, the accuracy is better. Moreover, if the optimal threshold is used to detect object, the accuracy is improved dramatically. The fixed threshold is easy to cause detection failure, especially when the surrounding is changing. We can conclude that the optimal threshold can adapt different circumstance, when the number of the object is different, it can give better detecting result, too.

The comparative detecting results between the traditional fixed threshold method and the new algorithm proposed in this paper are shown in figure 5.

In this paper, four images are given in two video sequence under indoor and outdoor circumstance. The influence of the light is different in the same video sequence when person at different position, so, the threshold should differ from each other. Figure5 (a) is original detected image, the left two images have one object under indoor circumstance and the right two images have two objects under outdoor circumstance. (b) is gray difference images after background subtraction. Since the position of the object is different, the noise is different in the same video sequence. (c) shows the binary image when the fixed threshold is 10. We can conclude from the result, if $T = 10$, there is noise in the detected images, and the indoor circumstance can give better result. Moreover, in the same video sequence, the detected result is different with the same threshold. In (d), the fixed threshold is 15 under indoor circumstance and is 25 under outdoor circumstance. We can see from the images that there is no noise, but, the object is incomplete, especially under outdoor circumstance. Additionally, we can see, in the four images, the first image can give best result. But, with the same threshold, the object is incomplete in second image. Simultaneously, in the right two outdoor circumstance images, the integrity of the same object in different image is unequal. So the fixed threshold is limited. (e) is the detected result with an optimal dynamic threshold which proposed in this paper. In fact, according to the new algorithm, we can calculate that the optimal threshold for the four images under indoor and outdoor circumstance is：

$T_1 = 13.831$， $T_2 = 13.145$， $T_3 = 21.560$， $T_4 = 22.827$

Figure5. Detecting result comparison in two video sequences under indoor and outdoor circumstance
(a) The original image under indoor and outdoor circumstance. (b) The gray difference image with background subtraction. (c) The detected result with fixed threshold 10. (d) The detected result with fixed threshold 15 and 25. (e) The detected result with optimal threshold.

The threshold has little change under indoors and great change under outdoors. When the light changes dramatically, the optimal threshold can suit the circumstance, too.

The distinction can be seen from the experiment results. The value of fixed threshold is unchangeable, so, if the surroundings change, an accurate detected result can not be obtained. But, if the threshold is dynamic and its value changes with the mean and variance of the image, the system can give an excellent result even if the circumstance is not steady.

So, in the same surveillance system, because the influence of the circumstance, the fixed threshold can't realize the detecting task accurately. If the system can not detect the object accurately from the background, the tracking task will fail. The algorithm proposed in this paper can overcome the effect of the light changing and separate the object from the background. The threshold which determined by the parameter of every image is an adaptive value, so, it can conquer the shortcoming that threshold is too big to ensure the object region integrated and the threshold is too small to remove noise from the binary image. The new method can give a better detecting result. The algorithm is based on statistical model, it can give a better detecting result without any filter. So, in the same surveillance system, because the influence of the circumstance, a fixed threshold can't realize the detecting task accurately. The optimal threshold proposed in this paper can separate the object from the background successfully. The threshold which determined by the parameter of every image is an adaptive value, so, it can conquer the shortcoming that the threshold is too big to ensure the object region integrated and the threshold is too small to remove noise from the binary image. The new method can give a better detecting result.

Ⅵ. CONCLUSIONS

When the object is detected in a same video sequence, because of the change of the light and other factors, a fixed threshold is limited, and the accuracy of the object detection will be affected greatly. In this paper, combined with likelihood function, according to Bayesian maximum risk estimation and optimal judgment criterion, a new dynamic threshold is obtained and the gray difference image is processed to detect object. The value of the threshold is determined by mean and variance of every image in the video sequence. It is proved by the experiment that the threshold can adapt the change of the surrounding, the new algorithm can restrain the noise effectively and finish the object detection accurately.

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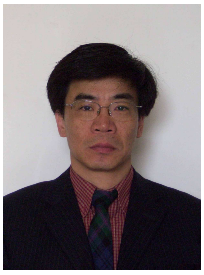

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