Journal of Computing and Electronic Information Management
ISSN: 2413-1660 | Vol. 10, No. 3, 2023

Infrared small target image segmentation based on hybrid Gaussian background modeling

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Abstract: Aiming at the problems of small infrared targets occupying few pixels and complex background interference, hybrid Gaussian background modeling is adopted. Since the background image between adjacent frames does not change much, the target change is displaced. The features of each pixel in the image are represented by K weighted Gaussian models, and when a new frame of image is obtained, the hybrid Gaussian model is updated, and each pixel in the current image is matched with the mixed Gaussian model, and if successful, the point is judged to be the background point, otherwise it is the foresight. Experiments show that using the weighting of multiple Gaussian model distributions to represent the background can better adapt to the complex environment.

Keywords: Complex background; IR small target; Mixed Gaussian.

1. Introduction

Infrared imaging has the advantages of long distance, high concealment, good anti-interference, strong ability to penetrate smoke, dust, fog and haze, and can work all weather and all day, so it is widely used in military fields such as surveillance, reconnaissance and navigation, and has become one of the main technologies in modern precision guided weapons. Detecting and tracking enemy targets at as far a distance as possible in order to attack at the most favorable time is an important factor in determining the outcome of modern warfare. The farther the distance, the smaller the target imaging area, and the image contains a complex background, which requires image segmentation technology to accurately segment small targets.

Aiming at the relatively stable detection platform, this paper constructs a multi-dimensional mixed Gaussian distribution model for each pixel based on the background model proposed by Stauffer et al., uses the inter-frame difference method to perform differential processing on the adjacent two frame images, and distinguishes the pixels in each frame into background area and change area through adaptive threshold. Then the points in the change area are matched with their multi-dimensional mixed Gaussian distribution, and then the background exposure area and the moving object area are distinguished. Relative to the background area, the pixels in the background exposed area will update the multidimensional mixed Gaussian distribution model with a large update rate. The points in the moving object region no longer construct a new Gaussian distribution and add it to the multidimensional mixed Gaussian distribution model; Update the background after learning new scene information. This method effectively compensates for the slow update speed of the adaptive hybrid Gaussian background model proposed by Stauffer et al. when the background of a stagnant object changes from the background to the foreground moving object. At the same time, the algorithm also attenuates the influence of slow-moving objects on the background model. The experimental results show that the hybrid Gaussian background modeling image segmentation algorithm can accurately segment small targets in complex backgrounds.

2. Model image segmentation based on mixed Gaussian background

Mixed Gaussian background modeling is a background representation method based on pixel sample statistics, which uses statistical information such as the probability density of a large number of sample values of pixels over a long period of time (such as the number of patterns, mean and standard deviation of each mode) to represent the background, and then uses statistical differences to determine the target pixels, which can model complex dynamic backgrounds. In a mixed Gaussian background model, the individual pixels are treated independently of each other. For each pixel in an image, the change in its value in a sequence image can be seen as a random process that continuously produces pixel values.

Using the hybrid Gaussian background model, the target change is shifted because the background image between adjacent frames does not change much. The features of each pixel in the image are represented by K Gaussian models, and when a new frame of the image is obtained, the hybrid Gaussian model is updated, and each pixel in the current image is matched with the mixed Gaussian model, and if successful, the point is judged to be the background point, otherwise it is the foresight. Gaussian models are mainly determined by two parameters, variance and mean, and different mechanisms for learning mean and variance will affect the stability, accuracy and convergence of the model. The mathematical expression of a mixed Gaussian model is:

$$P(X_t) = \sum_{i=1}^{k} \omega_{i,t}\, \eta\ (X_t, \mu_{i,t}, \sum i,\ t) \tag{1}$$

Generally, K takes between 3-5, $\omega_{i,t}$ is the weight of the ith part of time, $\eta(X_t, \mu_{i,t}, \sum i,\ t)$ represents the Gaussian function of the ith part of time t, $\mu_{i,t}$ and $\sum i,\ t$ represent the mean and covariance matrix of pixels, respectively.

$$\eta\ (X_t, \mu_{i,t}, \sum) = \frac{1}{\frac{n}{2\pi^2}|\sum|^{\frac{1}{2}}} e^{-\frac{1}{2}(X_t-\mu)^T \sum^{-1}(X_t-\mu)} \tag{2}$$

(1) Parameter initialization

In this paper, it is considered that the first frame of the video image is more likely to be the background of the scene, even if some areas of the first frame of the image are moving targets, relative to the entire image, the motion area only

occupies a small part, take the pixel value of the first frame image to initialize the mean of a Gaussian function in the Gaussian blending model, and take a relatively large value of the weight of the Gaussian function (more important than the weight of several other Gaussian functions), the mean of other Gaussian functions is taken as zero, the weight is equal and takes a smaller value, The variance of all Gaussian functions in a Gaussian mixture model takes an equal and large initial value, so in the learning process of Gaussian mixture parameters, it is more likely to take the mean of the Gaussian function with a larger weight as the background of the scene. Namely:

$$\mu = \frac{1}{N}\sum_{t=0}^{N-1} X_t \quad (3)$$

$$\sigma^2 = \frac{1}{N}\sum_{t=0}^{N-1}(X_t - \mu)^2 \quad (4)$$

μ represents the image mean gray value, σ^2 represents the variance, μ and σ^2 are used to initialize the parameters of the K Gaussian distribution in the Gaussian mixture model.

(2) Parameter update

The parameter update of the Gaussian mixture model is more complicated, it not only updates the parameters of the Gaussian function, but also updates the weights of each Gaussian function, and sorts the Gaussian functions according to the weight. When the input pixel satisfies equations 5, it is classified into the Gaussian model and preliminarily determined to be the background pixel.

$$\left|X_t - \mu_{i,\ t-1}\right| < 2.5\sigma_{i,\ t-1} \quad (5)$$

$\mu_{i,\ t-1}$ represents the mean of the i-th Gaussian function at time t-1, $\sigma_{i,\ t-1}$ represents the standard deviation of the ith Gaussian function at time t-1.

If the match is successful, update the Gaussian function parameters of the successful match as follows.

$$\omega_{i,t} = (1-\alpha)\omega_{i,t-1} + \alpha \quad (6)$$

$$\mu_{i,t} = (1-\rho)\mu_{i,t-1} + \rho X_t \quad (7)$$

$$\sigma_{i,t}^2 = (1-\rho)\sigma_{i,t-1}^2 + \rho(X_t - \mu)^T(X_t - \mu) \quad (8)$$

α is expressed as a custom learning rate with 0 <α <1, α determines the size of the background update speed, the larger α the faster the update speed, the smaller α, the slower the update speed. The α value of this paper is 0.01.ρ represents the learning rate of the parameters, and the $\rho \approx \frac{\alpha}{\omega_{k,t}}$. Mismatched Gaussian functions keep their mean and variance constant, weight decay, updated as:

$$\omega_{k,t} = (1-\alpha)\omega_{k,t-1} \quad (9)$$

If there are K Gaussian models where there is no matching Gaussian model, then the Gaussian with the smallest weight is replaced by a new Gaussian. The weighting of multiple Gaussian model distributions to represent the background allows for better adaptation to complex environments. Gaussian mixture modeling during background reconstruction is performed using K Gaussian models to characterize each pixel. For the Gaussian background model, iterative update is used for each newly entered image and background frame comparison.

(3) Divide the foreground background

Through the parameter learning mechanism of the Gaussian mixture model, those Gaussian functions with relatively large weights are used to describe the background pixels with higher frequency, while the Gaussian functions that describe the motion target are used with smaller weights. When all parameters of an image are updated, all Gaussian function weights are normalized, and then $\omega_{k,t}/\sigma_{k,t}$ of each Gaussian function is calculated, sorted from largest to smallest according to the value, the larger the weight, the higher the frequency, the smaller the variance means that the pixel value changes smaller, which is in line with the characteristics of the background, so the larger the $\omega_{k,t}/\sigma_{k,t}$, the greater the likelihood that it is the background distribution. Set a weight threshold, when $\omega_{k,t}/\sigma_{k,t}$>thresh is met, it is considered to be a background distribution, otherwise it is a motion target distribution. The thresh in this paper was obtained empirically by experiment, taking thresh = 0.75.

3. Experiment and analysis

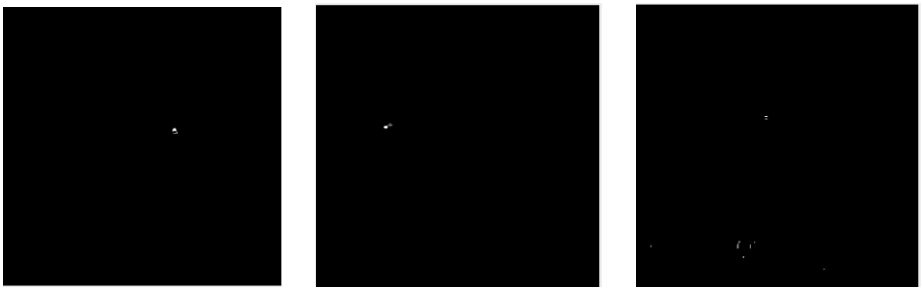
The image segmentation method based on hybrid Gaussian model is experimented, and the adaptive threshold segmentation method is compared, and some experimental results are shown in Figure 1:



(a)Original



(b)Adaptive threshold segmentation



(c)Mixed Gaussian

Fig. 1 Comparison of image segmentation methods based on hybrid Gaussian model

As can be seen from Figure 1, the image segmentation method based on mixed Gaussian background modeling has a better segmentation effect than the adaptive threshold segmentation method. Basically, the background is effectively suppressed

4. Summary

In this paper, hybrid Gaussian background modeling is used to successfully segment small targets under the interference of complex backgrounds. However, this is not true for large variations in the background area between adjacent frames. The next step will be further optimization, and when the detection platform is shaken sharply, small targets can still be effectively segmented.

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