Detection method of moving object pig based on difference method and energy minimization

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Abstract: In order to improve the real-time and accurate rate of pig detection in monitoring video, a new moving object pig detection algorithm is proposed in static background. Combining the Adaptive Threshold Three-Frame Difference Method and the Background Update Difference Method based on Energy Minimization Theory, do the "and" operation to the difference, do the "or" operation to the background difference of current frame and the result of "and", the complete information of moving object and continuous extraction of the pigs' contours can be obtained. Results of experiments show that the edge continuity index range obtained by this method is 0.7-0.9, while the edge continuity index ranges of the Traditional Three-Frame Difference Method and the Background Difference Method are 0.3-0.5, the detection results are improved remarkably. In this paper, the Background Update Method is combined with the Energy Minimization Segmentation algorithm, the principle is simple and it can help accurately get the contour information of moving objects while the contour extraction results are continuous and complete. This method can adapt to the object detection under complex scenes such as illumination changes, and it can meet the real-time requirements.

Keywords: moving object detection, three-frame difference, background difference, energy minimization

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1 Introduction

China is a large pig breeding country, according to statistics, statistics such as pig's stock rate, slaughter rate, pork yield are ranked first in the world (Wu et al., 2015). With the development of large scale and intensive farming, the risk of breeding has gradually increased. Real-time health status monitoring and daily activity recording of individual pig (Duan et al., 2015; Xiao et al., 2016) can help quickly find pigs' abnormal behavior and let appropriate measures be timely taken to reduce the occurrence of disease (Zhu et al., 2010; Porto et al., 2013).

Moving object detection is to remove the background content from the video image, detect the moving target and get its movement information. The accuracy and effectiveness of detection algorithm affect the correctness of identification of the moving target. So detection algorithm plays an important role in computer vision (Oczak et al., 2013; Zuriarrain et al., 2013; Ahrendt et al., 2011). Commonly used moving target detection algorithms in static background include Optical Flow Method (Lu et al., 2010), Background Difference Method (Alex et al., 2014), Frame Difference Method (Zhang et al., 2012) and so on. Frame Difference Method and Background Difference Method are widely used in moving object detection because of their simplicity, quickness and real-time. However, slow moving or stationary targets are easy to be missed when Frame Difference Method is used, and one cannot get complete target extraction when the grayscale or the texture of two consecutive frames are close because the "hole" and "double shadow" could appear. To solve this problem, Vieren et al. (1995) proposed a detection method based on three-frame difference, which improved the detection accuracy. Yin et al. (2011) proposed a fast target tracking method based on Mean Shift and Three Frame Difference

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Methods, which could effectively overcome the problem of false detection. Pang et al. (2013) put forward a moving object extraction algorithm based on Three Frame Difference and Canny edge detection which can get complete target information with good anti-noise performance. This method could effectively extract the moving object in real-time. Shu et al. (2014) proposed a Five Frame Difference method which reduced the "false detection" to some extent. The establishment and real-time updating of the background model in the Background Difference method is the key to the algorithm. Some researchers have put forward various algorithms for adaptive updating of the background, such as Frame Difference method (Gupte et al., 2002), Kalman Filter method (Messelodi et al., 2005), Single Gaussian Model (Liu et al., 2014), Hybrid Gaussian model (Zhao et al., 2015), etc. Rao et al. (2014) detected moving targets using the Three Frame Difference method and the Calman Filter. Guo et al. (2014) used the Hybrid Gaussian Model and Threshold Segmentation to obtain complete moving pig targets. Li et al. (2013) and Sun et al. (2014) used Adaptive Background Difference method and Three Frame Difference method based on the Kalman Filter Model to achieve real-time tracking of moving target. The above Background Update methods perform better in avoiding the interference of random noise and illumination changes. The shadow and reflection of the moving object will significantly change the shape of the detection target. The contrast between the foreground object and the obscured background area is not enough, the pixels in a frame cannot be clearly distinguished whether they are from foreground or background. Some researchers used Energy Minimization techniques (Boykov et al., 2001) in foreground detection, and this is an effective segmentation method. Malcolm et al. (2007) and Boykov et al. (2001) proposed Graph Cut for video segmentation, which required to specify the object to be detected in the first few frames before the detection, and use its information to detect further. This method achieved real-time and fast segmentation of targets. As time went on, some of the new moving objects in the video image would not be detected. Howe et al. (2004) proposed an automatic detection method based on Graph Cut, the operation time was longer, but the model design was simpler.

In the process of moving target detection, the Three-Frame Difference method is easy to cause the "hole" phenomenon and the Background Difference method is sensitive to the change of scene. This paper presents a detection method of moving target pig which combines Three-Frame Difference method and Background Difference method to extract whole moving area of target, introduces the Energy Minimization theory in Background Difference method, and builds an energy equation to solve the background update problem. The method has strong robustness to the illumination change and it can detect the pig target accurately (Navarrojover et al., 2009, Lind et al., 2005).

2 Algorithm principle

2.1 Improved Three-Frame Difference method

The Traditional Inter Frame Difference or Three-Frame Difference method is real-time, but the motion area extracted is incomplete, the target's contour is not continuous, a lot of holes would appear when detecting slow moving target. In order to improve the real-time and accuracy of pig identification in monitoring video, this paper presents an improved real-time target detection algorithm based on Three-Frame Difference. The algorithm is as follows Equation(1):

(1) Take an image every 3 consecutive frames $f_{i-3}(x,y)$, $f_i(x,y), f_{i+3}(x,y)$ i=4,5,6…;

(2) Transform into grayscale images respectively, and do the Gaussian filtering, median filtering in order to remove the noise of the image. Get the corresponding image $I_{i-3}(x,y)$, $I_i(x,y)$, $I_{i+3}(x,y)$;

(3) Get the difference respectively;

$$\begin{cases} d_{(i-3,i)}(x,y) = | I_i(x,y) - I_{i-3}(x,y) | \\ d_{(i,i+3)}(x,y) = | I_{i+3}(x,y) - I_i(x,y) | \end{cases} \tag{1}$$

where, $d_{(i-3,i)}(x,y)$ represents the difference image between the current frame and the frame before 2 frames, $d_{(i,i+3)}(x,y)$ represents the difference image between the current frame and the frame after 2 frames. If $I_{i-3}(x,y)$, $I_i(x,y)$ have the same frame order as $I_i(x,y)$, $I_{i+3}(x,y)$, then the calculation can be saved, $d_{(i-3,i)}(x,y)$ is same as $d_{(i,i+3)}(x,y)$.

(4) The difference image is binarized in Equation (2):

$$\begin{cases} b_{(i-3,i)}(x,y)=\begin{cases}1 & d_{(i-3,i)}(x,y)\geq T\\ 0 & d_{(i-3,i)}(x,y)<T\end{cases}\\ b_{(i,i+3)}(x,y)=\begin{cases}1 & d_{(i,i+3)}(x,y)\geq T\\ 0 & d_{(i,i+3)}(x,y)<T\end{cases}\end{cases} \quad (2)$$

where, T is the adaptive threshold, $b_{(i-3,i)}(x,y)$ and $b_{(i,i+3)}(x,y)$ are binary images after comparing the difference images and threshold T.

(5) In order to reduce the "hole" phenomenon, process the above binary result morphologically; in order to reduce the "overlap" phenomenon of the target, do the "and" operation to the corresponding pixel (x,y) in 2 binary images; eliminate the small "details" by morphological processing; get the binary image of the target's contour of the current frame. Equation (3):

$$B_i(x,y)=\begin{cases}1 & b_{(i-3,i)}(x,y)\cap b_{(i,i+3)}(x,y)=1\\ 0 & b_{(i-3,i)}(x,y)\cap b_{(i,i+3)}(x,y)\neq 1\end{cases} \quad (3)$$

where, $B_i(x,y)$ is the binary image of "and" operation.

2.2 Background Difference method of Energy Minimization

The basic idea of the Background Difference method is to establish the background model, and divide the current frame from the background image to obtain the moving target area. If the pixel threshold is greater than a certain threshold, it is determined that the pixel in the current frame is the foreground, otherwise is the background. The establishment and updating of background model is the key of background difference method.

2.2.1 Build background model

The background model is built to extract the initial background image, and prepare for the detection of the target. It directly affects the integrity of the moving target (Wang, 2011). This paper uses the method of multi frame image statistics to get the average value, which can greatly avoid the problem of detecting wrong clumps in the background detection when there is moving objects in the first frame. Take N consecutive frames' images in the sequence to calculate the average pixel (Wu et al., 2012) as Equation (4):

$$B_0(x,y)=\frac{1}{N}(K_1(x,y)+K_2(x,y)+\ldots+K_i(x,y)) \quad (4)$$

where, N is the number of sequence frames. N=50 in this paper. $K_i(x,y)$ is the grayscale image of i^{th} frame, $B_0(x,y)$ is the reconstructed background image. The value of each pixel in the background image is its cumulative average grayscale in N frames' images.

2.2.2 Background model update

With the influence of factors like illumination changes and scene changes, the background model should be able to adapt to changes in environment during a certain period of time, so it must be constantly updated. This paper presents an Energy Minimization method to update the background model in real-time so that the background can be updated to the corresponding background of the current video frame when moving objects merge into or move out of the background.

This paper uses manual interaction to specify the approximate region of specific target in the first frame. The Maximum Flow / Minimum Cut theory (Tokmakov et al., 2016, Wang et al., 2012) based on graph theory is adopted, the basic idea is: user forcibly define some "hard constraints", that is, mark some targets' pixels by hand, and set them to be the seed pixels to calculate the grayscale histograms of foreground and background; all the pixels (including the specified foreground, background seed pixels) are nodes of the graph, the adjacent pixels are the edges of the graph, and the difference between the pixels is the weight (grayscale value) of the edge, the network graph is constructed, as shown in Figure 1. By calculating the minimum cut in all segments, other pixels of the video frame are automatically classified into the target or background to complete the detection.

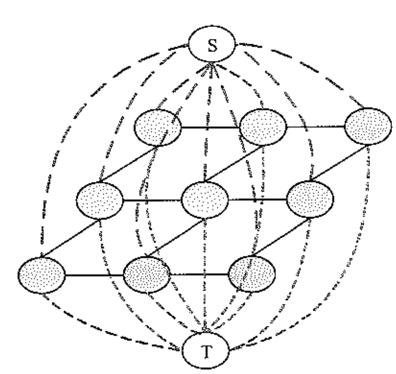


Figure 1 Energy minimization example

The energy function is Equation (5):

$$E(L)=\alpha R(L)+B(L) \quad (5)$$

where, $L=\{l_1, l_2,\ldots l_v\}$ represents the label vector of each pixel in the image, v is the vertex set of the graph, the value of l_i is 0 (background) or 1 (foreground), $\alpha\geq 0$ represents the correlation between the region attribute $R(L)$ and the boundary attribute $B(L)$, $R(L)$ is the intensity of the intensity model (gray histogram) that the pixel belongs to the known foreground or background, $B(L)$ is the weight between the pixel p and the pixel q. The goal is to obtain the L label vector when the $E(L)$ is the minimum.

(1) Calculate region term by Equations (6)-(8):

$$R(L)=\sum_{p\in P} R_p(l_p) \tag{6}$$

$$R_p(1)=-\ln\Pr(l_p\mid \text{'fkg'}) \tag{7}$$

$$R_p(0)=-\ln\Pr(l_p\mid \text{'bkg'}) \tag{8}$$

where, P represents the set of ordinary vertices; $P_p(1)$ represents the weight of the l_p is 1(foreground); $P_p(0)$ represents the weight of the l_p is 0(background); $\ln\Pr(l_p|\text{'fkg'})$ is the probability that the p belongs to the foreground; $\ln\Pr(l_p|\text{'bkg'})$ is the probability that the p belongs to the background.

(2) Calculate boundary term by Equations (9)-(11):

$$B(L)=\sum_{<p,q>\in P} B_{<p,q>}\sigma(l_p,l_q) \tag{9}$$

$$B_{<p,q>}=\frac{\exp\left(-\frac{(I_p-I_q)^2}{2\delta^2}\right)}{\text{dist}(p,q)} \tag{10}$$

$$\sigma(l_p,l_q)=\begin{cases}0 & \text{if } l_p=l_q\\ 1 & \text{if } l_p\neq l_q\end{cases} \tag{11}$$

where, p and q represent adjacent vertices; l_p is the tag value of vertex p; l_q is the tag value of vertex q; I_p and I_q respectively represent the gray value of the pixel p and q; δ represents the threshold for p and q brightness difference; dist(p,q) is the Euclidean distance between p and q; σ is the adjustment factor, if the p and q mark value are the same, then $\sigma=0$, otherwise $\sigma=1$.

2.3 Algorithm implementation

The detailed description of target pig detection algorithm based on the difference method and the energy minimization is as follows:

(1) Input / output image

Input the images in sequence; the detection result of each frame image in binary form is output.

(2) Improve Three-Frame Difference method to detect the contour of moving target pig

Select the interval 3 frames for the difference and set the adaptive threshold to get the binary image.

(3) Improve Background Difference method to detect the area of moving target pig

Background initialization phase: establish a background model of the background difference and specify the foreground pixel in the first frame image.

Background update phase: Update background model based on Maximum Flow / Minimum Cut theory in Energy Minimization.

Calculate the probability of each pixel in the current frame with foreground and background model; each vertex in the graph corresponded to each pixel in the frame, establish the edges between two terminal nodes and these vertices, create the edges between neighbor vertices and construct the network graph; according to the pixel value of each adjacent pixel and the obtained probability density map, the edges are weighted value; the energy minimization algorithm is performed on the corresponding graph to obtain the minimum cut. Calculate the energy value of the next frame, and compare with the previous frame energy value to achieve the background update.

(4) Post-processing phase

Use the mathematical morphological operation to make the movement area continuous, complete, and remove the noise in the background to obtain accurate moving targets.

(5) Contour acquisition phase

Obtain the complete contour image by using the target contour tracking algorithm (Yuan et al., 2010, Chen, et al., 2011), which is only able to track the inner boundary of the target image. In other words, the boundary is within the target, and the "hole" in the image could not be handled. We can accurately obtain the target contour information and it can provide more accurate data for the future behavior identification.

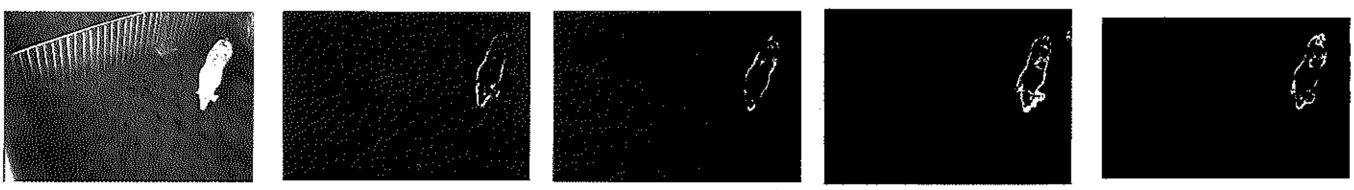
3 Results and discussion

The algorithm program is developed under Microsoft

Visual Studio 2010, Open CV 2.3.1. The hardware operating environment is Intel(R) Core(TM) i7-6700 CPU, running on a 4.00GB memory computer and 64-bit Windows7 system. Image resolution is 192×256, the video frame is 25 frames per second, which basically meets the requirement of real-time.

3.1 Frame interval analysis

For the objects moving fast, smaller intervals are needed. If the selection is not appropriate, when the object in the two consecutive frames there is no overlap, it will be detected as two separate objects. For the objects moving slowly, larger intervals should be chosen. If the time selection is not appropriate, the object will not be detected when the object is almost completely overlapped in the two consecutive frames. According to the activity characteristics of pigs (Hao et al., 2012), this paper uses interval of three frames to make difference. Calculate the difference between the adjacent three frames, and the moving region is detected accurately and effectively. It reduces the background noise and "missed detection" phenomenon, and improves the accuracy of moving target detection. Detection results shown in Figure 2.



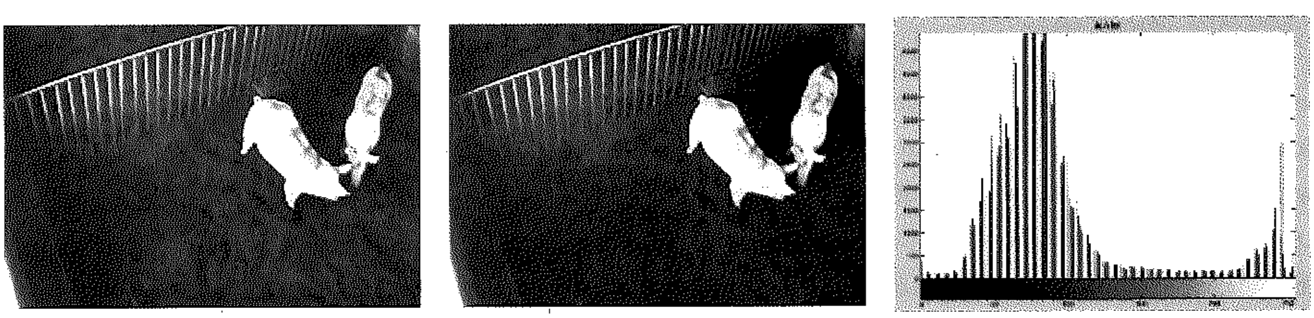
a. 19th frame b. Interval 1 frame c. Interval 2 frames d. Interval3 frames e. Interval 4 frames

Figure 2 19th frame threshold segmentation effect

As can be seen from Figure 2, the Traditional Three-Frame Difference method (Figure 2b) and the two-frame interval method (Figure 2c) obtained obscure contours of moving object, in which a lot of "holes" appeared; this paper (Figure 2d) selects three-frame interval method to do the difference, and can obtain a complete target; if four-frame interval (Figure 2e) is used, the moving position of the object is quite different with the expansion of the interval, the target cannot be accurately detected and the detection effect becomes worse.

3.2 Threshold analysis

The grayscale image and the gray histogram of the video image are shown in Figure 3. According to the graph, the gray characteristics of the pig in the video image are obviously different from the background gray scale, the peak and trough of the gray histogram are very obvious. Otsu algorithm (Otsu, 2007, Yang et al., 2009) is simple and has fast processing speed, and it is used to obtain the threshold for the image with obvious double-peak gray histogram. This paper adopts Otsu algorithm to obtain the threshold.

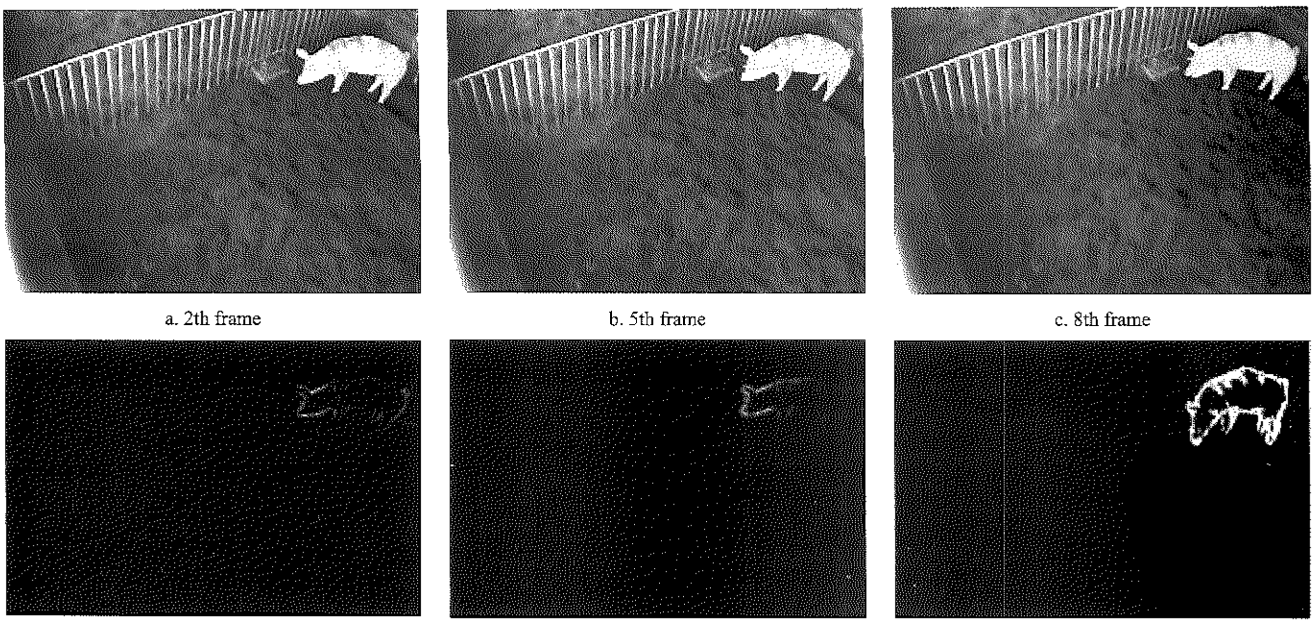


a. Video original image b. Video image grayscale c. Video image gray histogram

Figure 3 Grayscale and gray histogram of video image

Figure 4 shows the color image of moving pig and the threshold image segmentation effect of the Otsu algorithm. From the results of binarization, the threshold obtained by the OTSU algorithm can segment the pig contour more completely, and it provides the basis for the follow-up pig detection.

In Figure 4, three images (Figure 4a, Figure 4b and Figure 4c) are collected by three-frame interval method to make the differential experiment. Figure 4d is the difference result between the 2th frame and the 5th frame, Figure 4e is the difference result between the 5th frame and the 8th frame, and Figure 4f is the two difference images with "and" operation, and use Otsu method to get binary image. By setting the adaptive threshold, the information in the difference image is more prominent, and the contour of the moving object is clearer. The Otsu method can segment the difference image precisely, and the probability of the background error is greatly reduced.



a. 2th frame b. 5th frame c. 8th frame

d. 2th frame and 5th frame difference image e. 5th frame and 8th frame difference image f. Otsu method

Figure 4 Threshold segmentation effect

3.3 Background update analysis

This paper uses the mean method to build initial background, a rapid background extraction can be achieved. It has less computation and can realize object detection more real-time. The initial background is shown in Figure 5.

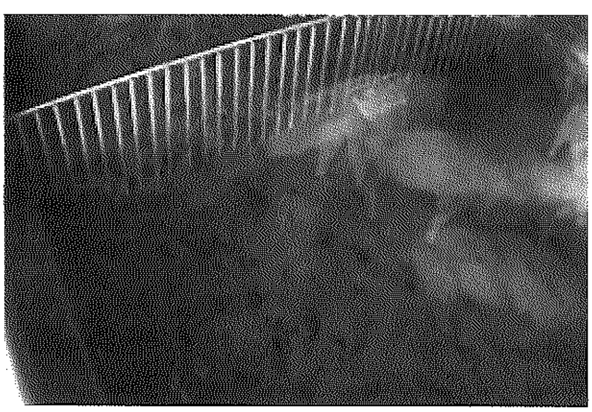


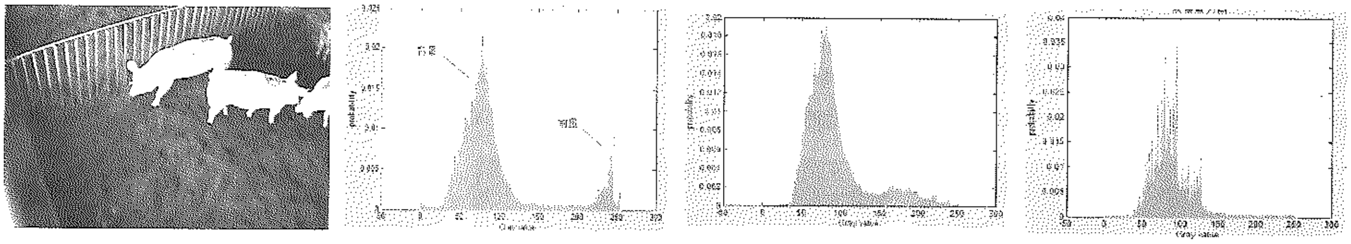
Figure 5 Initial background

In order to better illustrate the accuracy and effectiveness of the proposed method, the current frame and background image are intercepted in the video, as shown in Figure 6, and the background image is analyzed, as shown in Figure 7.

Figure 6a is a color image in the video sequence, and Figure 6b is the background image obtained by the Traditional Background Difference method. It can be seen from the figure that the Traditional Background Difference method has serious "double shadow" phenomenon, which increases the difficulty of the subsequent target extraction. In this paper, the background updating image based on the energy minimization method can adapt to the changes of light and background, the phenomenon of double shadow is greatly reduced.

a. Original frame b. Background difference method c. New approach

Figure 6 52th frame background update effect



a. Original frame b. Gray histogram of the original frame c. Gray histogram of the background difference method d. Gray histogram of the new approach

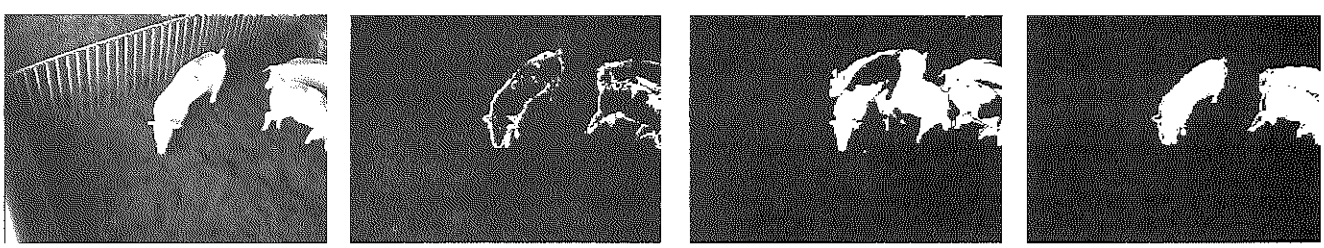
Figure 7 364th frame original frame and background gray histogram

Based on the analysis of the video frame and background image in Figure 6, it is concluded as follows: By specifying the target pig in the first frame, the foreground gray value range is obtained, as shown in Figure 7b. The background gray histogram obtained by the Traditional Background Difference method as shown in Figure 7c, the gray histogram is focused on the background pixels and has a large amount of foreground pixels; this paper uses energy minimization idea of graph cut to update background model in real-time. From Figure 7d can be seen that the background gray value range is close to the original video frame gray histogram, and the foreground pixel is less. It shows that the method performs better in updating background.

3.4 Detection results analysis

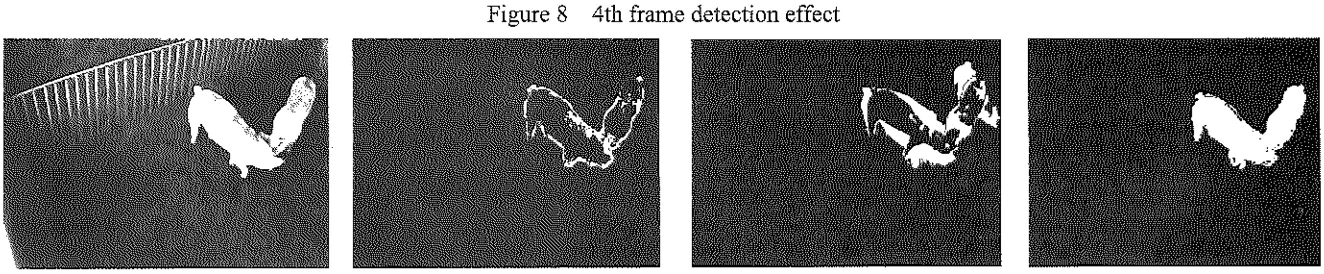
3.4.1 Intuitive analysis

In order to verify the effectiveness of the improved detection algorithm, the motion objects of surveillance video are detected in real-time, and the algorithm is verified by nearly 80000 frames in the video image. The Three-Frame Difference method, the Background Difference method and the improved method are used to experiment with different video sequences of the same scene. The contrast results are shown in Figures 8-10. Use the contour detection operator for contour detection, the contours of the moving target are shown in Figures 11-13. The sample are 4th, 226th, 465th frame captured in the video.



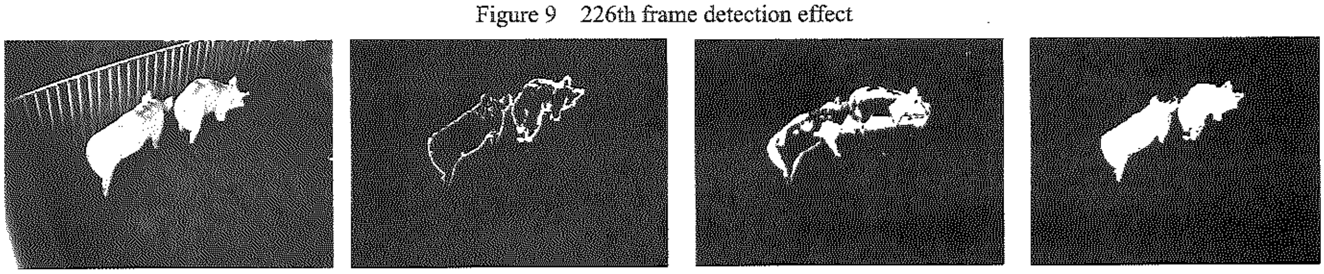
a. Original frame b. Three frame difference c. Background difference d. New approach

Figure 8 4th frame detection effect



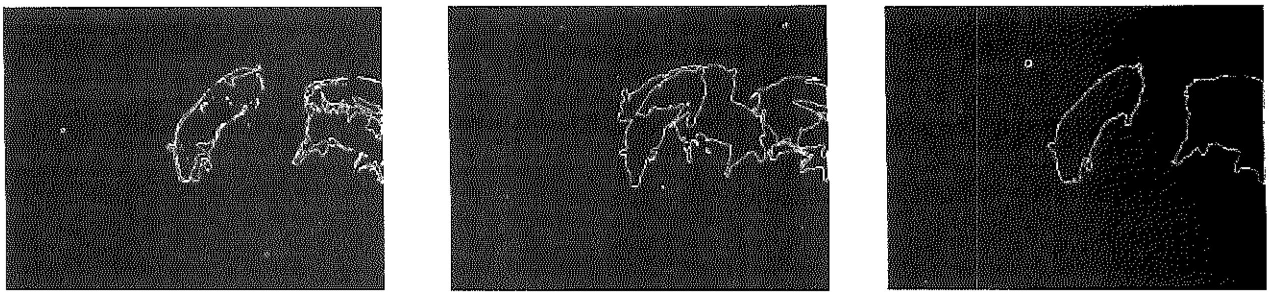
a. Original frame b. Three frame difference c. Background difference d. New approach

Figure 9 226th frame detection effect



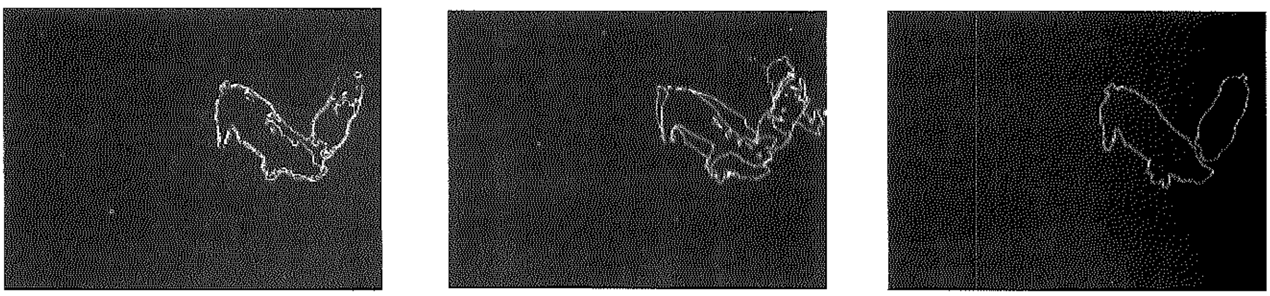
a. Original frame b. Three frame difference c. Background difference d. New approach

Figure 10 465th frame detection effect



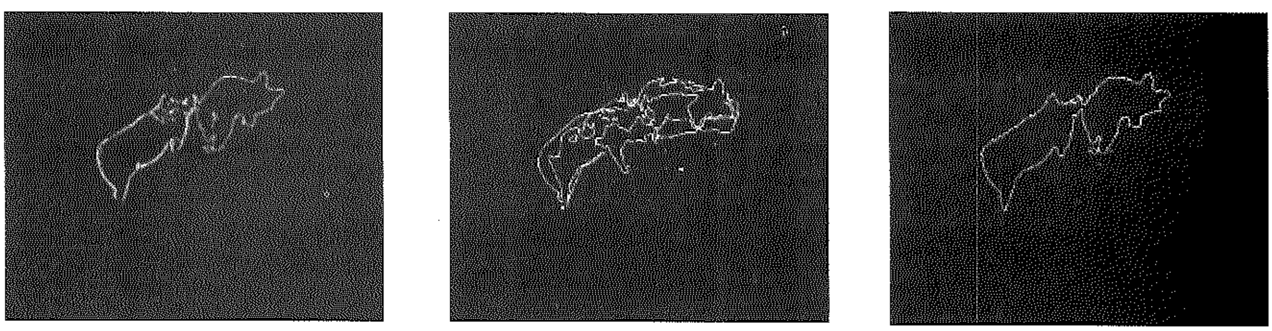
a. Three frame difference b. Background difference c. New approach

Figure 11 4th frame contour detection effect



a. Three frame difference b. Background difference c. New approach

Figure 12 226th frame contour detection effect



a. Three frame difference b. Background difference c. New approach

Figure 13 465th frame contour detection effect

From the experimental results, it can be seen that the moving objects based on the Three-Frame Difference method and the Background Difference method have "hole" phenomena and accompanied by noise, as shown in Figure 8b, Figure 9b, Figure 10b and Figure 8c, Figure 9c, Figure 10c. It cannot extract the complete area of the moving target, it is difficult to obtain a complete target contour, and the detection effect is not accurate; this method is more complete to extract the moving target area of pigs, the phenomenon of "hole" and "double shadow" is less, it can describe the contour in detail and reduce the influence of noise.

Edge continuity refers to the continuity of the edge image detected by the edge detection algorithm. If the detection effect is good, each section of the image has a large spatial range, and the continuity is good. If the detection effect is not good, the edge appears fracture or broken, the continuity is bad. As can be seen from Figures 11-13, the Three-Frame Difference Method and the Background Difference Method are used to obtain the contour image discontinuity, as shown in Figure 11a, Figure 12a, Figure 13a and Figure 11b, Figure 12b, Figure 13b; the contour image extracted by this method is more complete and continuous, it is consistent with the target image and has better detection effect.

3.4.2 Quantitative analysis

In order to evaluate the objective performance of the proposed moving object detection algorithm, we use the edge continuity evaluation index (Duan et al., 2016) to analyze different detection algorithms, which is commonly used in literature. Edge continuity refers to existence the edge pixels in the eight neighborhood of the pixel, and the degree of continuity is defined by the number of edge pixels that exist (Zhu, 1996), which directly affects the identification of moving objects.

For the edge binary image W, it is assumed that the number of consecutive edge segments is m, the i segment is composed of the pixel set $C_i = \{W(x_1^i, y_1^i), W(x_2^i, y_2^i), ...W(x_{n_i}^i, y_{n_i}^i)\}$. The value of the edge segment pixel $W(x_k^i, y_k^i)$ to its edge segment continuity is in Equations (12):

$$c_k^i = \begin{cases} d_k^i / D & d_k^i < D \\ 1 & d_k^i > D \end{cases} \quad (12)$$

where, d_k^i is the distance from the edge pixel $W(x_k^i, y_k^i)$ to the edge space center $(\overline{x_i}, \overline{y_i})$; D is the distance threshold, which can be selected according to the image size and scale.

In order to facilitate the comparison between multiple images, the normalization process is used to satisfy the continuity index range access to [0, 1]. Mo et al. (Mo et al., 2011) constructed the S-function and defined the continuity of the edge segments in Equations (13):

$$SC^i = S(C^i) = 2 \times (\frac{1}{1 + \exp(-C^i / \alpha)} - 0.5) \quad (13)$$

where, C^i is the sum of the continuity of all the pixels in the i segment. After a large number of experimental data testing; α take 2 is the most appropriate.

The continuity index reflects the relationship between the number of edge segments and the length of each edge. Edge detection image continuity index is Equations (14):

$$CIdx = \sum_{i=1}^{m} (n_i \times SC^i) / \sum_{i=1}^{m} n_i \quad (14)$$

where, n_i is the number of pixels in the i edge segment.

Select the first 1000 frames of the video as the display test data, as shown in Figure 14.

The value range of the image continuity index range (CIdx) is [0, 1]. The smaller the value, the worse the continuity of the edge detection image. The bigger the value, the better the continuity of the edge detection image. As can be seen from Figure 14: (1) The Three-Frame Difference method and the Background Difference method are significantly lower than the detection algorithm in this paper, which indicates that the target detection error is large. It cannot get complete and continuous target. (2) According to the continuity index data: The continuity index range of the Traditional Three-Frame Difference method and the Background Difference method are 0.3-0.5. The continuity index range of this method is 0.7-0.9. The contour continuity is improved obviously, and the contour extraction results are accurate, complete and with good robustness.

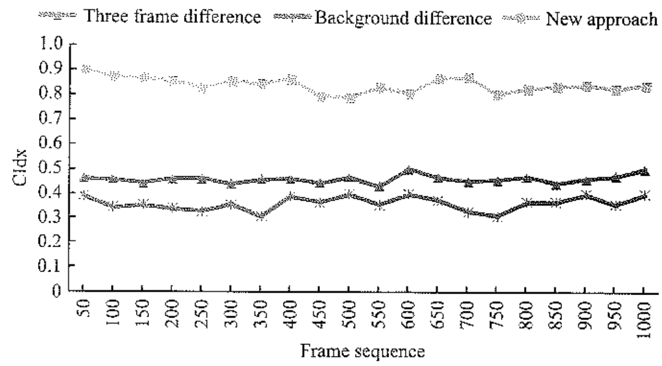


Figure 14 Contrast of Contour Continuity

3.5 Algorithm efficiency analysis

In order to analyze the detection efficiency of different moving object detection algorithms. This paper selected six monitoring videos for experiment, and the average execution time of three different algorithms are shown in Table 1.

Table 1 Different algorithms efficiency comparison results

Video sequence	Frames	Three frame difference	Background difference	New approach
		Running time, s Efficiency, fps s^{-1}	Running time, s Efficiency, fps s^{-1}	Running time, s Efficiency, fps s^{-1}
1	74980	3279.97 22.86	3584.13 20.92	3734.06 20.08
2	78502	3408.68 23.03	3729.31 21.05	3901.69 20.12
3	74855	3320.98 22.54	3455.91 21.66	3750.25 19.96
4	84907	3732.18 22.75	4047.04 20.98	4123.70 20.59
5	78510	3575.14 21.96	3682.46 21.32	3877.04 20.25
6	82515	3639.83 22.67	3839.69 21.49	3955.66 20.86
average value		22.64	21.24	20.31

The data in Table 1 shows that the algorithm is stable and effective, the average execution time of different moving object detection algorithms are respectively: The Three-Frame Difference method is 22.64 fps/s, the Background Difference method is 21.24 fps/s, and this method is 20.31 fps/s. In this paper, fusion the Three-Frame Difference method and the background difference method, and transform the background update problem of the Background Difference method into the image segmentation energy minimization. With the single pixel as processing, the background update time is increased. Compared with the Traditional Background Difference method, this method uses more time and the efficiency is decreased. The segmentation method can detect moving target effectively and meet the requirements of real-time detection.

4 Conclusion

Aiming at the shortcomings of traditional difference method motion target detection algorithm, this paper proposes a three frame difference and energy minimization background difference fusion algorithm. It can be seen from the detection effect that the moving target detection algorithm can detect the complete target pig accurately and extract the continuous contours of the target pig. The main findings of the experiment are summarized as below:

(1) The principle of the algorithm is simple, it can completely detect the moving target of different environment and different speed. The algorithm overcomes the phenomenon that there are empty holes in the Traditional Three-Frame Difference Method, and eliminates the "ghost" and the "drag" phenomenon of the Background Difference Method. The edge continuity index range of this method is 0.7-0.9, the edge continuity index range of the Traditional Three-Frame Difference method and the Background Difference method are 0.3-0.5. The continuity of the contour is improved obviously.

(2) Through the analysis of different video detection efficiency, this method slows down the operation speed compared with the Traditional Three-Frame Difference method and the Traditional Background Difference method, it still satisfies the real-time detection. The findings proposed in this paper provide technical support for the target tracking and the monitoring, and it provides the basis for evaluation, warning.

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