Target detection method for moving cows based on background subtraction

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Abstract: Target detection is the fundamental work for perceiving the behavior of cows using video analysis automatically. The videos captured in farming scenes often suffer from a complex background, which leads to difficulty in detecting the target and inconvenience in the subsequent images analysis. In this study, a method was proposed to detect the moving target accurately for cows based on background subtraction. Firstly, the bounding rectangle of cows was calculated using the frames difference method to extract the local background in frames, which were averaged and spliced into one image as the entire background image. Secondly, the size and location of a cow's body were determined by the bounding rectangle of cows, and the body area was tracked through the video by the binary images. Thirdly, the summation coefficients on RGB channels were adjusted to improve the contrast between the target and background images. Finally, taking the body area in every frame as reference area, the performance of target detection was evaluated by the reference area to determine the optimal summation coefficients on RGB channels, and then background subtraction was processed again to finish the detection. A total of 129 videos were used to test the detection algorithm, and the accuracy of the algorithm was 88.34%, which was 24.85% higher than the classical background subtraction method. The study shows that the algorithm proposed in this study is feasible to detect the target accurately and timely when cows are walking straight in the farming environment under natural light, and this method can improve the detection performance and is an extension to the classical background subtraction method.

Keywords: moving cows, target detection, background subtraction, image analysis, target tracking, video analysis

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1 Introduction

Video analysis techniques developed from intelligent surveillance applications have been widely used in the field of stock farming[1-4]. Research on the use of these techniques for perceiving and recognizing the behavior of cows automatically for precise dairy farming has become a hot topic such as detection of lying behaviour[5], feeding behaviour[6,7], and oral behaviour[8]. Especially, the lameness detection[9-11] and locomotion[12,13] of cows have been widely discussed in a series of studies. Aiming at segmenting the object from video frames to track and analyze it in the subsequent processing, detection of the target is the foundation of recognizing the behavior of cows using video analysis.

As sun angle and light reflection on the background influence the video capturing of the cows in an opening farming environment, the brightness changes greatly between video frames. Additionally, the difference of gray values between the target and background becomes closer when the cows are contaminated by mud. The complicacy of illumination and environment conditions requires new target detection algorithms. Background subtraction[14,15], frames difference[16,17] and motion estimation[18,19] are the most common target detection methods. In the background subtraction method, the

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background is obtained by background modeling, which is subtracted from the images to detect the target. Accordingly, the background subtraction method is sensitive to the difference between the target and the background. The frames difference method is used to calculate the difference between several successive frames to find the moving outline of the target, and it is difficult to obtain the entire area of the target. Motion estimation methods are designed by using complicated physical models based on the constant brightness rule, which are unusable to analyze the behavior of cows because of the high processing time and lower detection accuracy. Therefore, it is important and necessary to develop a new method adapting to the farming environment for accurately detecting cows.

In this study, a series of algorithms were proposed to detect the moving target accurately for cows based on background subtraction. Firstly, the bounding rectangle of cows was calculated using the frame difference method to extract the local background in frames, which were averaged and spliced into one image as the entire background image. Secondly, the size and location of a cow's body were determined by the bounding rectangle of cows, and the body area was tracked through the video by the binary images. Thirdly, the contrast between the target image and the background image was improved by adjusting the summation coefficients on RGB channels, and the background was subtracted from the adjusted target image. Finally, taking the body area in every frame as reference area, the performance of target detection was evaluated by the reference area to determine the optimal summation coefficients on RGB channels, and then background subtraction was processed again to finish the detection.

2 Materials and methods

2.1 Experimental materials and setup

Video data in MP4 form were collected on a commercial dairy farm in Yangling, China in August 2013. Videos of Holstein cows in mid-lactation time were captured from 8:00 to 14:00 on sunny days. After milking, side-view images were acquired while cows were passing through a 2 m wide, 7 m long aisle with a concrete floor to a water trough. Videos were recorded using a DS-2DM1-714 integrated IP camera (Hikvision Inc., Hangzhou, China), and the range of the focal length of the lens is 3.84-88.4 mm. To avoid any intrusion into the farm's routine and any interference with cow traffic, the camera was positioned on the supported beam of a feeding shed at a height of 1.8 m and 35 m away from the alley. The CCD sensor was parallel to the corridor, which permitted a side view of the cows. And the focal length was set to 45 mm to assure that the width of the field of view was twice the length of one single cow. Color videos were captured in QuickTime H.264 compressed format, with frame rate of 25 fps and code rate of 2 048 kbps at a resolution of 704 × 576 pixels. The acquisition of one single video began at the appearance of the whole cow, and ended when the cows moving to the edge of the field of view. In total, 129 videos were captured with an average duration of 20 s. The algorithms in this study were developed in MATLAB 2012a. The moving area of cows was fixed in the middle section in the vertical direction of the field of view. Accordingly the unnecessary area was eliminated using default ROI (region of interest) parameters. The size of the final images to be analyzed was 704×242 pixels.

2.2 Background modeling

In every frame, the areas outside the bounding rectangle of cows were local background, which were merged into one image as the entire background image.

The frames difference method was feasible to calculate the moving edge of the target, and the images were processed to obtain the rough outline of the cows by the frames difference method. A binary morphology method and a threshold of image density were used to eliminate the external interference and influence of the swing on the tail.

To avoid the random error caused by the frames difference method, the bounding rectangle was extended 5% along the width and height direction, respectively. Because the width of the field was larger than twice the length of a single cow, the local background in each frame was merged into the entire background image. The results of locating the cow and extracting local background were shown in Figure 1.

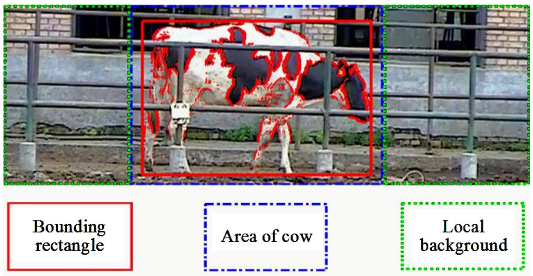


Figure 1 The location of body, cows and local background

The average of each pixel within the local background in every frame through a video was calculated to merge the local backgrounds into an entire background. Using the single channel image as example to simplify the description, the process of background modeling was shown in Figure 2, where the *Bk* is one channel of the entire background image in a video, and f_n is the image of the new frame from the video.

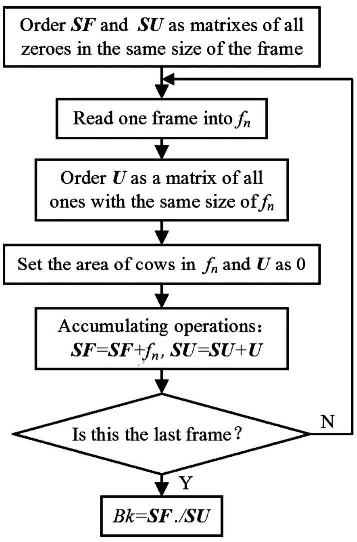


Figure 2 Processing of calculating the background using one channel

Each channel in the RGB color image of cows was processed to obtain the background image for the channel using the methods in Figure 2, and the background images from the three channels were integrated into one background color image.

2.3 Locating Body

The shape and image features of a cow's body were constant when cows were walking in the side view images. The size and location can be calculated by the bounding rectangle of cows. Locating and tracking the body was the fundamental work to detect cow target in high accuracy.

In the side view images, the size of the body area was fixed. m_b and n_b were taken as the width and height of the cow's body, respectively. The ratio of m_b to the cow's length was defined as r_a, and the ratio of m_b to n_b was defined as r_{mn}. Moving a rectangle sized $m_b \times n_b$ from top-left to bottom-right within the bounding rectangle of the cow's outline in Figure 3, as soon as the rectangle (marked with blue dash-and-dot lines in Figure 3) was tangent to the outline of cows, the body area was located.

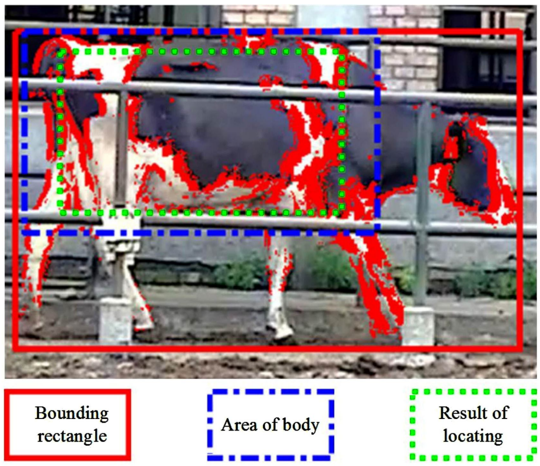


Figure 3 Result of locating a cow's body

After measuring 20 cows and experimental verification, r_a and r_{mn} were determined to be 0.75 and 1.75, respectively. The located body area was zoomed into 80% of it with a base point on center to remove the section of the background in the periphery of the body area. The result of locating the body was shown in Figure 3.

2.4 Tracking body

Considering that the shape of body area changed slightly when cows were walking through the video with translational motion on the body, the image tracking method was used to obtain the body image in subsequent frames to improve the efficiency in extracting body area. Meanshift[20] and the filter tracking algorithm[21] are two common methods to track a moving target in videos, but the filter tracking algorithm was time-consuming for tracking cows. As black and white were the main colors on cows' body, and the background contained excessive color information, the Meanshift algorithm based on color histogram was sensitive to the variation of color, which resulted in frequent tracking in the background area. It was found that Meanshift algorithm failed to track the body image accurately in the experiment. Therefore, in this study a method for tracking cows' body based on the binary image was proposed. The location of body area in the previous frame was used to find the image which was associated with the original image as the body area in the current frame. Using the located body area, the original image was extracted from the RGB image of cows, and was taken as f_0. In the next frame, the body area was extended 5% of it at all four directions with the base point at the center as the searching area, from which all images with the same size of f_0 were extracted as f_m, and were compared to f_0 using Equation (1). The evaluation of differences between two images was used to find the associated image to the original one, and the new body area was used to determine the searching area in the next frame.

$$\begin{cases} bf_0 = gf_0 > T, bf_m = gf_m > T \\ p = \text{numel}(bf_0 \cap bf_m) \end{cases} \quad (1)$$

where, bf_0 and bf_m are the binary images of gf_0 and gf_m, respectively; gf_0 and gf_m are the gray images of f_0 and f_m, respectively; T is the threshold for segmenting white area of a cow's body; 'numel' is the function to calculate the number of elements equal to 1 (TRUE) in a binary matrix; p is the evaluation of differences between the two images, and the larger the p, the closer the two images will be.

T was determined as 150 through experiment and test, which was feasible to find the new body image using the evaluation of difference calculated by Equation (1). The body images were steadily tracked in a short time with high accuracy.

2.5 Target detection

In the classical background subtraction method, the gray images of the background and the target were subtracted and segmented into a binary image using a threshold to find the different area for target detection. Generally, the Otsu's method was used to calculate the optimum threshold separating the two classes of pixels (foreground pixels and background pixels) by searching the threshold that minimized the intra-class variance (the variance within the class).

As cows were fed in a complex opening environment, the gray values of the target and the background may be close in spite of large difference on display between the RGB images of the target area and the background, which would result in failure in detecting the target. In addition, the HSV color model was tested, and the result showed that it was difficult to accurately detect the cow target using the hue value in complex brightness and environment conditions.

Therefore, the cow and background images were adjusted real-time using the summation coefficients on RGB channels, and the target was detected by subtracting the adjusted images. As shown in Equation (2), the gray value of a pixel was the linear summation on the three channels of the RGB image, so multiplication coefficients were adjusted to improve the contrast between the target and background images.

$$\begin{cases} Gray = \alpha R + \beta G + \gamma B \\ \alpha + \beta + \gamma = 1 \end{cases} \quad (2)$$

where, α, β and γ are the multiplication coefficient of R, G and B channels, respectively.

Defining D and $B_{m\times n}$ as evaluation area and body images, respectively ($D \in B_{m\times n}$), α, β and γ were ranged from -1 to 1 and the sum of α, β and γ was 1. The evaluation value, which was defined as $P_{\alpha,\beta,\gamma}$ in each group of coefficients, was calculated using Equation (3).

$$\begin{cases} gb = \text{Gray}(Bk), gf = \text{Gray}(ft) \\ Dfb = (gf - gb)^2 \\ P_{\alpha,\beta,\gamma} = \text{mean}(Dfb(i,j)) \quad i, j \in D \end{cases} \quad (3)$$

where, Bk is the background image; ft is the image containing the target; 'Gray' is a function to adjust images using Equation (2); gb and gf are the adjusted images of Bk and ft, respectively; Dfb is the difference image between gf and gb; 'mean' is a function to calculate the average of entire elements in a dataset.

As $P_{\alpha,\beta,\gamma}$ was a function with α, β and γ as variables, all possible values of the variables were applied into the function to search the maximum of $P_{\alpha,\beta,\gamma}$ and the corresponding values of α, β and γ as the optimal summation coefficients, which were used to adjust the target and background images. Then the background subtraction method was used to detect the target using adjusted images, in which the segmenting threshold was determined by the Otsu's method.

Experiment and test showed that a group of the summation coefficients was unable to improve the contrast of the two images in all gray value ranges. For instance, one group of the parameters, which was able to improve the contrast of the pixels in the black level, might reduce the contrast of the pixels in the white level.

In order to improve the contrast of pixels in every gray value range, the body area was divided into several non-overlapping sections which were defined as D_i by gray levels to replace the evaluation area. The optimal group of the summation coefficients for each section was calculated using Equation (3), and background subtraction was operated several times using different groups of the parameters to obtain parts of the target, which were combined as the detection result of the cow target. In this study, the body area was divided into three sections using Equation (4).

$$\begin{cases} D_1 = \{(i,j) \mid f_B(i,j) \le 85\} \\ D_2 = \{(i,j) \mid 85 < f_B(i,j) < 170\} \quad i,j \in B_{m\times n} \\ D_3 = \{(i,j) \mid 170 \le f_B(i,j)\} \end{cases} \tag{4}$$

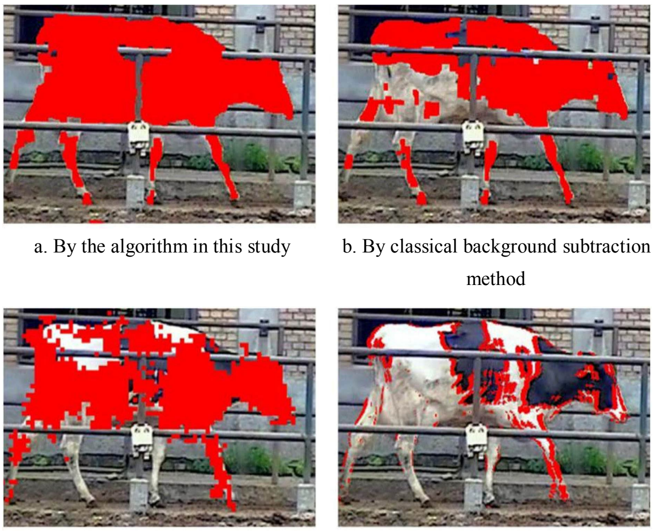
where, f_B is the gray image of a cow's body area, $B_{m\times n}$ is the body area in the frame.

Identification of the target shadow was important in the detection of a moving target. In this study, the cows were videoed in direct sunlight conditions with an eye-level shooting angle, so that the shadow of the target was behind the target with little exposure in the field of view. Furthermore, the entire background merged with the local background contained the shadow information of every position of the target. Based on the analysis above, the influence of shadow on target detection was negligible in this study.

3 Results and discussion

Total 129 side-view videos of cows were used to test the detection method which was compared with classical background subtraction, block matching and frames difference. To ensure the comparability between four methods, the thresholds in methods were determined by the Otsu's method respectively. An example of the detection result of the four methods is shown in Figure 4.

Five evaluation indicators were used to evaluate the performance of the four methods for detecting the cow targets[22], including true detection rate (TDR), false detection rate (FDR), false detection frames (FDF), refused detection frames (RDF) and processing time (PT). The target was segmented manually from frames to obtain the prospect target area which was taken as At, and Aa was defined as the target area detected by algorithms. At and Aa were used to calculate the five evaluation indicators by Equations (5)-(9).



a. By the algorithm in this study b. By classical background subtraction method

c. By block matching method d. By frame difference method

Figure 4 Performance of four target detection methods

The true detection rate was the proportion of pixels correctly detected by the algorithm among the all pixels segmented manually, which was calculated as follows:

$$TDR = \text{mean}(Aa_i / At_i)\times 100\% \tag{5}$$

where, Aa_i is the target area detected by algorithms in i^{th} frame; At_i is the prospect target area segmented manually in i^{th} frame, 'mean' is a function to calculate the average of the values in each frame. TDR is true detection rate in a frame, %. The larger TDR was, the more completely the target was detected in the frame.

The false detection rate was the proportion of pixels detected as the target by the algorithm but belonging to the background actually among the all pixels not belonging to At, which was calculated as follows:

$$FDR = \text{mean}(|Aa_i - (Aa_i - At_i)| / At_i^c)\times 100\% \tag{6}$$

where, At_i^c is the complementary set of At_i. FDR is the false detection rate in a frame, %. The less the FDR, the higher the detection accuracy.

The false detection frames calculated the number of frames with the false detection rate larger than 0.15, which measured the detection methods' suitability on the diversification in the environment. And it was calculated as follows:

$$\begin{cases} setFe = \{FDR_i \mid FDR_i > 0.15\} \\ FDF = \text{length}(setFe) \end{cases} \tag{7}$$

where, *setFe* is the set of false detection, 'length' is a function to calculate the number of elements in a set. *FDF* (frames) is the number of false detection frames in a video.

The refused detection frames calculated the number of frames with the true detection rate less than 0.55, which measured the detection methods' suitability on the contrast between the target and background. And it was calculated as follows:

$$\begin{cases} setFr = \{TDR_i \mid TDR_i < 0.55\} \\ RDF = \text{length}(setFr) \end{cases} \tag{8}$$

where, *setFr* is the set of refused detection. *RDF* (frames) is the number of refused detection frames in a video.

The processing time was the average of the time consumed in processing each frame through a video, which measured the work efficiency of algorithms. And it was calculated as follows:

$$PT = \text{mean}(t_i) \tag{9}$$

where, t_i is time consumed in processing i_{th} frame, s; *PT* is the processing time of a video, s.

All videos were processed to obtain 129 groups of evaluation indicators, and the average of each indicator is shown in Table 1.

Table 1 Comparison of four different detection methods

Detection method	$\overline{TDR}$ /%	$\overline{FDR}$ /%	$\overline{TDF}$ / frames	$\overline{FDF}$ / frames	$\overline{PT}$ /s
Method in this study	88.34	0.76	0.22	0	0.15
Background subtraction	63.49	0.81	0.27	27.43	0.02
Block matching	46.60	6.52	30.23	92.85	1.99
Frames difference	11.66	2.29	9.55	129.36	0.01

Note: Because the cows were covered by the barrier through the video, the accuracy of target detection was less than 95% theoretically. $\overline{TDR}$, $\overline{FDR}$, $\overline{TDF}$, $\overline{FDF}$, and $\overline{PT}$ are the average values of *TDR*, *FDR*, *TDF*, *FDF* and *PT* over all the samples, respectively.

As shown in Figure 4 and Table 1, with short processing time but low detection accuracy, the frames difference method was merely sensitive to the strong motion edge. Over half of the target can be detected by the classical background subtraction method, but it was difficult to segment the target accurately when the gray levels of the cows and the background were close. The block matching method was based on motion estimation; accordingly target detection may fail when the cows were moving slightly or not moving, which resulted in decrease in true detection rate and increase on refused detection frames. And diversification of brightness and the camera shake had a great influence on the detection result of the block matching method leading to a large false detection area which resulted in a high false detection rate and numerous false detection frames. Although the processing time of the method proposed in this study was merely lower than that of the block matching method, the proposed method had the highest true detection rate among the four methods, and it also had a lower false detection rate, less false detection frames and refused detection frames than the other three methods.

The distribution of the true detection rate using the algorithm in this study is shown in Figure 5. The *TDR* of the samples distributed in a nearly normal fashion, and the average of overall *TDR* was high with a small standard deviation, indicating that the algorithm was reliable and stable.

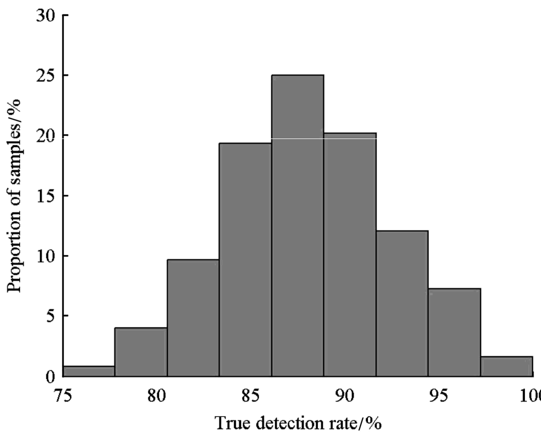


Figure 5 Distribution of true detection rate using the algorithm in this study

The improved value of target detecting in a frame using the algorithm in this study against the old method was calculated by subtracting the true detection rate of the classical method from that of this algorithm. Taking each frame as a sample, the improved values of all the samples consisted in a sequence, whose span was divided into 10 equally spaced containers and the proportion of the elements in each container are shown in Figure 6. The *TDR* using the new algorithm increased, and the improved values distributed from 15% to 35% with an average of 24.85%, indicate that the algorithm has a great improvement over the classical background subtraction method.

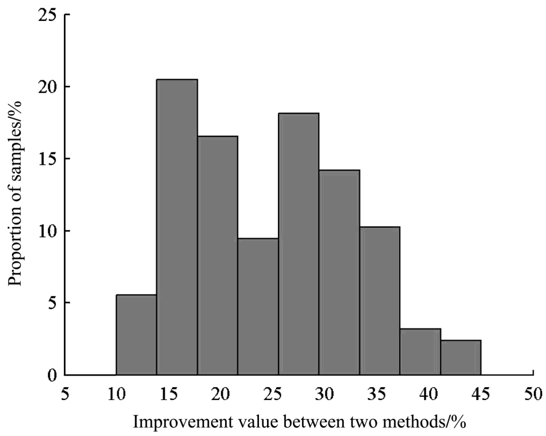


Figure 6 Distribution of improved value between algorithm in this study and classical background subtraction method

In this study, the pure background frames without the target were dispensable in the background modeling process, and the local background in each frame was used to reduce the influence of diversification of brightness and shadow on target detection. This algorithm was feasible to accurately and effectively detect the target when cows were walking straight in natural light and a farming environment, and it may have the potential for detecting moving animals in complex environments.

4 Conclusions

1) The bounding rectangle of a cow's outline was used to extract the local background in each frame, and the local background was averaged and spliced into one image as the entire background image. The background modeling method was independent of the pure background frames without the target, which can be used to extract the background in complex scenes. As the background contained the information of brightness and shadow in each frame, the interference from an external environment in the target detection process was avoided.

2) To overcome the sensitivity of the image tracking method on diversification of color, an evaluation parameter was designed to compare the difference between the original and new image. When the threshold for target tracking was determined as 150 through experiment and test, it was feasible to find the new body image using the difference evaluation. The body images were steadily tracked in a short time with high accuracy.

3) Taking the cow's body area as an evaluation region, the summation coefficients on RGB channels were adjusted to improve the contrast between the target and background images, and the background was subtracted from the adjusted target image to detect the target cows. The true detection rate of this algorithm was 88.34% with a high improvement over the classical background subtraction method. The algorithm in this study was feasible to detect target with a low contrast between the target and background.

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