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A Traffic Motion Object Extraction Algorithm

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A motion object extraction algorithm based on the active contour model is proposed. Firstly, moving areas involving shadows are segmented with the classical background difference algorithm. Secondly, performing shadow detection and coarse removal, then a grid method is used to extract initial contours. Finally, the active contour model approach is adopted to compute the contour of the real object by iteratively tuning the parameter of the model. Experiments show the algorithm can remove the shadow and keep the integrity of a moving object.

Keywords: Background difference; active contour model; shadow detection; dilate; erode.

1. Introduction

With the development of economy and the advancement of urbanization, intelligent transportation plays an increasingly important role. For traffic information, real-time detection can obtain wealthy information and data, such as traffic flows, speeds, queuing situations, etc. These data provide strong evidence for errorless traffic management strategies. At present, main approaches for vehicle detection are coil detection, infrared sensor detection, radar detection, video detection, etc. As a video-based detection system does not need to undermine the roads but can obtain continuous video information, according to a series of video processing such as detection, segmentation and real-time tracking of moving vehicles, it can analyze and summarize various traffic parameters in a more rational and effective way. Therefore, video-based traffic detection has become an important technique.

For the traffic image sequences attained by detection in video images, researchers propose a variety of techniques on vehicle detection, such as background subtraction [Hou, 2005] and frame difference [Haritaoglu, 2005], etc. In the actual traffic scenes, the accuracy of moving target detection is also affected by the moving shadows. Because moving shadows along with moving targets move together, frame difference and background subtraction cannot directly and accurately decollate the moving targets. Accuracy of moving object extraction has a great influence on subsequent treatments. For these reasons, this paper proposes a more accurate moving object extraction algorithm.

2. Algorithm Flow

The algorithm flow is as in Fig. 1.

Above all, it extracts the moving regions to enter image frames by the utilization of classical background subtraction. It detects and eliminates the shadows in the moving areas, then attains the initial contour, finally, it approaches the real contours of moving objects by the utilization of active contour model and acquires the segmentation results.

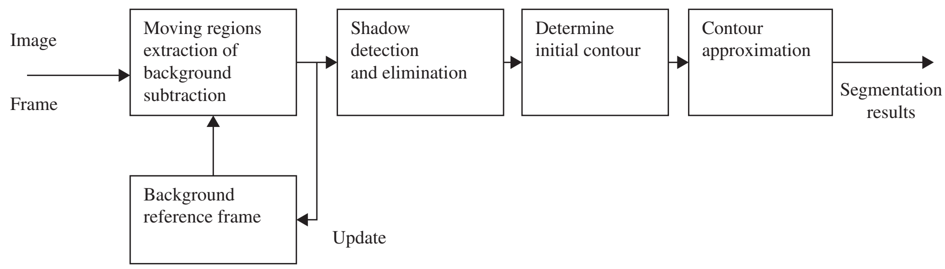


Fig. 1. Flowchart of moving object extraction.

3. Moving Object Extraction of Traffic Scene

3.1. *Motion detection*

Moving object extraction means coarse segmentation for the vehicles of video images in traffic scenes, and it decollates the possible vehicle areas for subsequent operations. This algorithm employs background subtraction to obtain the moving regions; whose cogitation is that to first generate the background images of traffic scenes, and then subtract pixel by pixel the images waiting to be checked against the background image and acquires the difference image Diff.

$$\mathrm{Diff}(i,j) = |\mathrm{Cur}(i,j) - \mathrm{BG}(i,j)|. \tag{1}$$

Equation (1), $\mathrm{Cur}(i,j)$ represents the pixel value of current frame at i, j column, $\mathrm{BG}(i,j)$ represents the pixel value of background reference frame at i, j column, $\mathrm{Diff}(i,j)$ represents the pixel value of difference image at i, j column.

In the difference image Diff, it can acquire the segmentation image (MA) by the utilization of threshold technique. The difference image is the binary image, the white part represents the moving region, and the black part is the background.

$$\mathrm{MA}(i,j) = \begin{cases} 1 & \text{If } \mathrm{Diff}(i,j) \geq TH \text{ motion} \\ 0 & \text{others.} \end{cases} \tag{2}$$

In Fig. 2(a), the background image BG attained by the above background acquisition and updated algorithm can be seen, Fig. 2(b) is the image Cur waiting for detection, Fig. 2(c) is the moving segmented image. Judging from Fig. 2(c), the moving regions contain not only the vehicles, but also the moving shadows.

3.2. *Detection and elimination of shadow*

Because of the moving shadow and the inaccurate moving targets extracted as in Fig. 2(c), these factors have great influence on subsequent processing, thus some approaches must be taken to eliminate shadows to improve the precision of moving object extracted. At present, there have been many techniques on studying separation of the shadow object to detect the shadow regions, such as color change technique, texture invariant technique and local brightness variation technique, etc. The literature proposes a core density estimation model based on RGB color space to eliminate shadows in color videos. Generally, the image signal collected by the camera is based on the YUV color space, so the above techniques needing transformation of the color space is not conducive to real-time extraction. The important feature of the YUV color space is the separation of its luminance signal Y and chrominance signals U, V. It means the image is grayscale if only the signal Y is existing.

The image pixels are divided into two parts after motion detection, and one is the background,

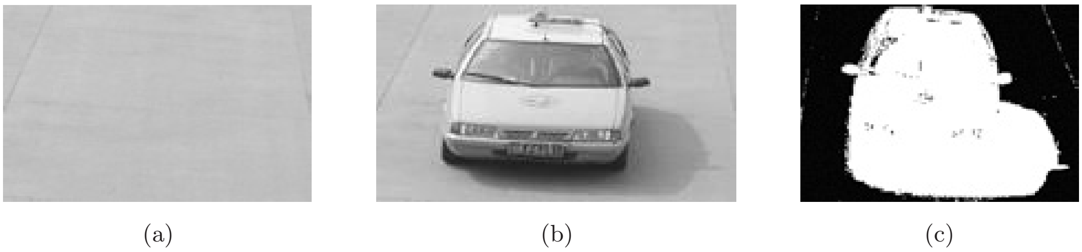
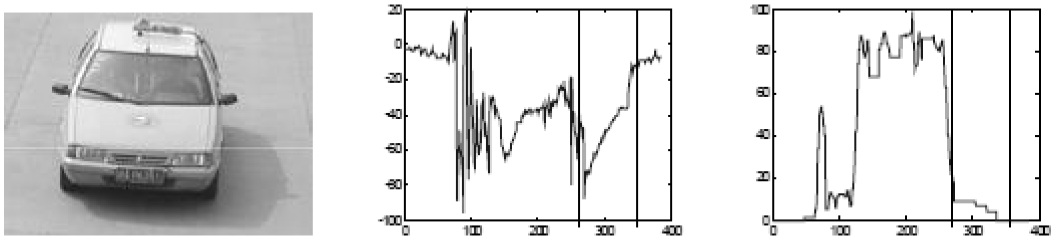


Fig. 2. Moving object extraction. (a) Background, (b) image to be checked and (c) moving segmentation image.



(a) (b) (c)

Fig. 3. Shadow detection. (a) Image to be divided, (b) brightness variation and (c) color variation.

the other is the moving region. Because the moving region may include moving shadow, it must detect the shadow and eliminate the shadow if existing. From Fig. 3(a), the brightness of images in the shadow region is reduced, and its color is altered only slightly.

LCHG(i, j) denotes the brightness variation between the detection frame and background reference frame at i, j column, whose formula is as shown below.

$$\mathrm{LCHG}(i, j) = \mathrm{Cur}(y, i, j) - \mathrm{BG}(y, i, j). \quad (3)$$

In the above formula, $\mathrm{Cur}(y, i, j)$ represents the strength of signal Y of current frame at I, j column, $\mathrm{BG}(y, i, j)$ represents the strength of signal Y of current background reference frame at I, j column. CCHG(i, j) represents the color change of detection frame and background reference frame at I, j column, whose formula is as below.

$$\mathrm{CCHG}(i, j) = |(\mathrm{Cur}(u, i, j) - \mathrm{BG}(u, i, j)| + |\mathrm{Cur}(v, i, j) - \mathrm{BG}(v, i, j)|. \quad (4)$$

In the above formula, $\mathrm{Cur}(u, i, j)$ and $\mathrm{Cur}(v, i, j)$ denote respectively the strength of signals U and Y of current frame at I, j column. $\mathrm{BG}(u, i, j)$ and $\mathrm{BG}(v, i, j)$ denote respectively the strength of signals U and Y of current background frame.

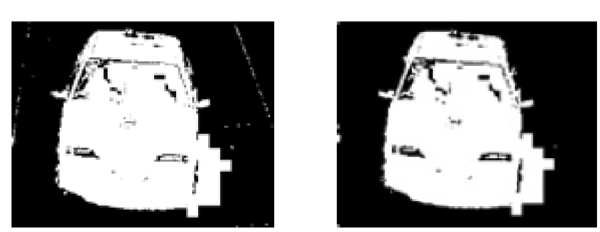
In Fig. 3, (a) is the image waiting to be detected, (b) is the variation LCHG of brightness on the white line in Fig. 3(a), Fig. 3(c) is the variation CCHG of color on the white line in Fig. 3(a). The range between the vertical bars in Figs. 3(b) and 3(c) is the shadow region. From Fig. 3(b), the image brightness in shadow region is reduced when LCHG < 0, from Fig. 3(c), the variation of color is little.

According to the characteristics of the shaded area, the steps of shadow elimination algorithm are as follows:

(1) Calculate the pixel whose value is 1 in MA employing the formula (3), corresponding with the brightness variation LCHG of pixels in the image waiting for segmentation.
(2) Calculate the pixel whose value is 1 in MA employing the formula (4), corresponding with the color variation LCHG of pixels in the image waiting for segmentation.
(3) Set the segmentation thresholds of brightness THL1 and THL2, and the segmentation threshold of color THC. If in the current pixels, THL1 $\leq$ LCHG $\leq$ THL2 and CCHG $\leq$ THC, the current point is judged as the shadow, and set its pixel value as 0 at the corresponding position. Otherwise, the current is judged as the moving object, and set its pixel value as 1 at the corresponding position.
(4) Repeat the steps (1)–(3) until all the pixels are scanned in MA, and it attains the new moving region image MA2.

Due to noise or other factors, there may exist small regions or holes in the image whose shadows are eliminated. This paper employs morphology to process this problem. Firstly, erode MA2, and then dilate it to gain the processed image MA3.

Figure 4 is the effective image after shadow elimination. MA2 is acquired by the utilization of shadow elimination algorithm in Fig. 4(a), from



(a) (b)

Fig. 4. Shadow removal. (a) Shadow elimination and (b) shadow elimination processed.

the figure, there exist isolated boundaries. MA3 is acquired by utilization of morphology in Fig. 4(b), the noise and isolated boundaries are eliminated basically.

3.3. *Contour extraction*

The initial contour of moving object can be extracted after the moving region MA3 is attained. Because of car window, there may exist some holes in the moving region. This paper employs the technique based on grid to extract complete contour. Divide MA3 into a grid with height GH and width GW, and then calculate the activity of each grid. The activity is defined as follows.

$$\text{Active}(x, y) = \sum_{i=x}^{x+Gw} \sum_{j=y}^{y+GH} \text{MA3}(i, j). \tag{5}$$

$\text{Active}(x, y)$ denotes the activity of grid at x, y, $\text{MA3}(i, j)$ denotes the pixel value at I, j. The Active is applied to detect whether the current grid belongs to the moving region or not.

Figure 5 utilizes this algorithm to extract the initial contour. Figure 5(a) utilizes 8×8 grid. Figure 5(b) utilizes boundary tracking algorithm to attain the initial contour.

3.4. *Contour approximation*

After the initial contour is attained, the algorithm of this paper utilizes active contour model to approach the true contour of the moving object. Active contour model also called Snake model was proposed by Kass to implement object segmentation based on edge. It defines the energy function reflecting target contour and image gray information, and it seeks the local minimum of self-energy function to make the initial contour close to the real contour gradually. Without prior knowledge, it approaches actively to attain the closed on target, smooth, continuous outer contour line. The activity contour seeks the local minimum of self-energy function to make the initial contour close to the real contour gradually. The activity contour is a collection of images, and is denoted as:

$$V = \{v_1, v_2, \ldots, v_l\}. \tag{6}$$

The total energy function of dynamic contour is defined as:

$$\begin{aligned} E_{\text{snake}} &= \sum_{i=1}^{l} E(v_i) \\ &= \sum_{i=1}^{l} [E_{\text{int}}(v_i) + E_{\text{ext}}(v_i) + E_{\text{con}}(v_i)] \end{aligned} \tag{7}$$

where

$$E_{\text{int}}(v_i) = \alpha E_{\text{cnt}}(v_i) + \beta E_{\text{cur}}(v_i) \tag{8}$$

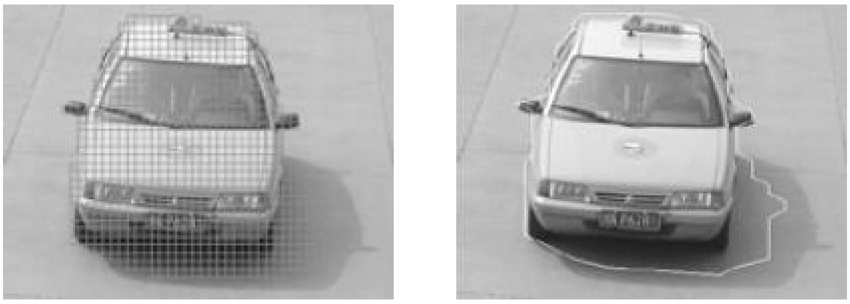
$$E_{\text{ext}}(v_i) = \omega * \text{Edge}(v_i) \tag{9}$$

$E_{\text{con}}(v_i) = -\gamma(x_i - x_c)^2$ 10.

Internal energy E_{int} is the local smoothing of curve Snake, winding curve phenomenon does not occur. The first item of internal energy E_{cnt} denotes the smoothness stretched, the second item E_{cur} denotes contour curvature. α and β are weighting constants. For open nonclosed curve, the internal energy tends to a straight line. For closed curve, the internal energy makes it shrink from outside to inside. In external energy E_{ext}, ω is weighting coefficient, Edge is the edges energy of the image, which can be attained by the following formula:

$$\text{Edge}(v_i) = -|\nabla f(v_i)|^2. \tag{10}$$

In the formula (11), $\nabla f(v_i)$ denotes the Image gradient at v_i. Edge attracts the curve to the edge. Econ is external constraint energy which attracts the points on the contour to some point of the



(a) (b)

Fig. 5. Contour extraction. (a) Activity grid and (b) initial contour.

image. Because the initial contour extracted contains the objects to be split, energy constraint is devised to shrink the curve. Therefore, x_c of external energy can be selected as the center of the closed curve, thus the curve can automatically shrink.

This paper employs greedy algorithm to solve active contour model. The point in contour can iteratively approach the object boundaries by solving an energy minimization problem. For each point v_i' in the field of v_i (include v_i), calculate the energy item below:

$$Ei(v_i') = E_{\text{int}}(v_i') + E_{\text{ext}}(v_i') + E_{\text{con}}(v_i'). \quad (11)$$

Select the lowest energy point as the current best position. For the first item E_{cnt} of internal energy, its standardized form is as the following:

$$E_{\text{cnt}}(v_i) = \frac{\bar{d} - |v_i - v_{i-1}|}{\max_j\{\bar{d} - |v_{ij} - v_{i-1}|\}}. \quad (12)$$

In the above formula, $\{v_{ij} \mid j = 0, 1, 2, \ldots, 8\}$ denotes the current contour point v_{i0} and its eight neighborhood points, $|v_i - v_{i-1}|$ denotes the distance among adjacent contour points. d denotes the average distance among all the contour points. For the second item E_{cur} of internal energy, its standardized form is as the following:

$$E_{\text{cur}}(v_i) = \frac{|v_{i-1} - 2v_i + v_{i+1}|^2}{\max_j\{|v_{i-1} - 2v_{ij} + v_{i+1}|^2\}}. \quad (13)$$

In the formula (14), the meaning of each item is similar to the above. Also for the external energy, that is, the intensity gradient, its standardized form is as the following:

$$\text{Edge}(v_i) = \frac{\min - |\nabla f(vi)|^2}{\max - \min}. \quad (14)$$

In the formula (15), max and min denote respectively the maximum and minimum gradients in the current field. Greedy algorithm can obtain quickly approximate optimal solution, whose complexity is only $O\ (nm)$, in which n is the number of contour points in the active model, m is the number of iterations.

Because the parameter α, β, ω is difficult to determine in greedy algorithm, often prone to excessive contraction in profile or cannot meet the actual profile and internal tension is not easy to balance the tension of image features. Therefore, the motion edge points in the original greedy algorithm are inducted to restrict the external tension. During profile searches, if the contour points reach the edge of motion, then mark the current contour point as edge, no longer moving. In sports edge image, the contour points are not able to reach the edge since the fractured edge employs the original greedy algorithm. The above improvement can be a good solution to the problem of excessive contraction.

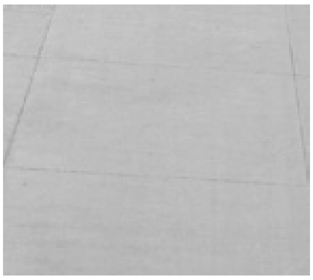
4. Experiment and Analysis

According to previous theoretical analysis and algorithm description, this paper tests the actual traffic images. In the experiments, according to experience, the threshold THmotion for motion detection is set to 20, THL1 for shadow detection is set to -100, THL2 is set to -1, THC is set to 10. In the contour extraction, the image is divided into 8×8 grid and THActive is set to 20. After the initial contour is extracted, the active contour model employs greedy algorithm to approach the edge for moving object. In the iterative process of active contour, weighting constants are respectively $\alpha = 1.0$, $\beta = 1.2$, $\omega = 1.8$, $\gamma = 1.6$.

The amount of computation of this algorithm is less than shadow elimination technique based on HSV color space. That is because the collected JPEG images which are decompressed do not need be converted from the time-consuming YUV color space to the HSV color space to operate. Moreover, in the elimination of shadows, the incompletion of shadow elimination can be effectively reduced or the excessive elimination probability to make the segmentation of target more accurate. Figure 6 is the effect of experimental comparison algorithm.

Figure 6 illustrates the experimental comparison employing the algorithm. Figures 6(a)–6(c) respectively are the background of Figs. 6(d) and 6(g), 6(e) and 6(h) and 6(f) and 6(i). Figures 6(d)–6(f) are the moving targets employing the algorithm proposed in this paper, Figs. 6(g)–6(i) employ the HSV color space to extract the motion background. It can be seen from the figures, this algorithm is smoother than the algorithm extracting the moving target in the HSV space whose target boundary appears sawtooth.

The main computations in this algorithm are the background and extracting moving target. When approaching contour, the greedy algorithm is utilized and boundary limit is introduced thus preventing excessive contraction and increasing the approaching speed. From the experimental results, this algorithm can well approach the moving objects; moreover, the extracted contour


(a) Background 1


(b) Background 2


(c) Background 3


(d) Extracted image 1


(e) Extracted image 2


(f) Extracted image 3


(g) Extracted image 1


(h) Extracted image 2


(i) Extracted image 3

Fig. 6. Experiments.

is closed, with smooth curves. This algorithm is implemented by the utilization of Visual c++6.0 and Pentium III 1.7G platform. And the image resolution is 400×400, processing speed measures up to 42F/S, which can reach real-time processing requirements.

5. Conclusion

An accurate contour extraction algorithm of moving object is proposed, which is proved in experiment not only to possess the fast computation speed, but also to acquire the closed and smooth object contours. In the previous processing of this algorithm, shadow elimination algorithm is employed to acquire the initial contour, and then the active model based on greedy algorithm is utilized to approach the true contour. The constraint of external tension in the process of approximation is introduced to prevent the contour from excessive shrinkage. However, as the far edge from contour point in active contour model cannot radiate the energy to the current contour and not attract the contour point to the true contour, the algorithm cannot expand outwards to approach the true edge when the initial contour is incomplete. In the future, new external energy function will be devised to make the image edge far from the contour point to radiate the energy to the contour point, thus making the contour point approach the complete object contour when the initial contour is incomplete.

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References

Haritaoglu, I. [2005] "Real-time surveillance of people and their activities," *IEEE Trans. PAMI* **22**, 809–810.

Hou, Z. Q. [2005] "A background reconstruction algorithm based on pixel intensity classification," *J. Softw.* **16**, 1568–1569.