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Study on a traffic motion object extrication algorithm

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ABSTRACT

In intelligent transport system, it is very important to precisely segment motion object from complex scene. Background difference and frame difference are two classic motion object extraction algorithms. If there are shadows associated to moving objects, both of the methods can't extract moving object precisely. With this problem, this paper proposes a motion object extraction algorithm based on active contour model. The following steps are performed in the proposed algorithm. Firstly, moving areas involving shadows are segmented with classical background difference algorithm. Secondly, perform shadow detection and coarsely removal, then using grid method to extract initial contours. Finally, use active contour model approach to 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 moving object.

KEYWORDS

Background difference; Active contour model; Shadow detection; Dilate; Erode.

INTRODUCTION

With the development of economy and the advancement of urbanization drive, intelligent transportation will play an increasingly important role. For traffic information, real-time detection can obtain wealthy information and data, such as traffic flow, speed, queuing situation, etc. These data provides strong evidence for errorless traffic management strategy. At present, the main approaches for vehicle detection are coil detection, infrared sensor detection, radar detection, video detection, etc. As video-based detection system needs not to undermine the road and can obtain continuous video information, according to a series of video processing such as the detection, segmentation and real-time tracking of moving vehicles, it can analyze and summary the various traffic parameters on 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 image, researchers propose a variety of technique on vehicle detection, such as background subtraction[1] and frame difference[2-3], 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 moves together, frame difference and background subtraction can't directly and accurately decollate moving targets. Accuracy of moving object extraction has a great influence on subsequent treatment, thus this paper proposes a more accurate moving object extraction algorithm.

ALGORITHM FLOW

The algorithm flow is as the Figure 1.

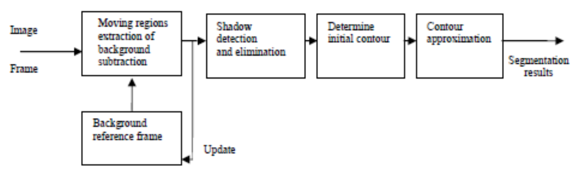


Figure 1 : Flowchart of moving object extraction

Above all, it extracts the moving regions to entered image frames by the utilization of classical background subtraction, meanwhile, Update the background reference frames, the background reconstruction algorithm employs the algorithm of literature[3]. 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.

MOVING OBJECT EXTRACTION OF TRAFFIC SCENE

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 the subsequent operations. This algorithm employs background subtraction to obtain the moving regions; whose cogitation is that firstly generates the background images of traffic scenes, and then subtracts pixel by pixel the images waiting for checking with background image and acquires the difference image Diff.

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

Equation (1), $Cur(i,j)$ represents the pixel value of current frame at i, j column, $BG(i,j)$ represents the pixel value of background reference frame at i, j column, $Diff(i,j)$ 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.

$$MA(i,j) = \begin{cases} 1 & If Diff(i,j) \geq THmotion \\ 0 & others \end{cases} \tag{2}$$

In Figure 2(a), it references the background image BG attained by the above background acquisition and update algorithm, Figure 2(b) is the image Cur waiting for detecting, Figure 2(c) is the moving segmented image. Judging from the Figure2(c), the moving regions contain not only the vehicles, but also the moving shadows.

(a) Background **(b) Image to be checked** **(c) Moving segmentation image**

Figure 2 : Moving object extraction

Detection and elimination of shadow

Because of the moving shadow and the inaccurate moving targets extracted as the Figure2（c）, these 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 camera is based on the YUV color space, so the above techniques needing transforming 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 existing.

The image pixels are divided into two parts after motion detection, and one is the background, 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 the Figure 3(a), the brightness of images in the shadow region is reduced, and its color is altered only slightly.

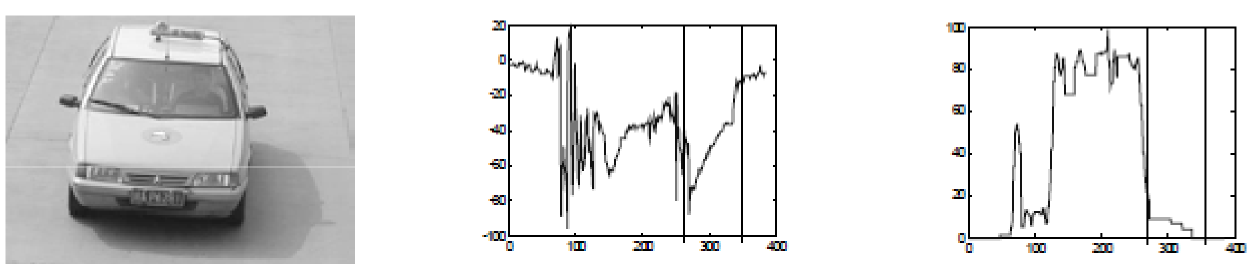
$LCHG(i, j)$ denotes the brightness variation between the detection frame and background reference frame at i, j column, whose formula is showing bellow.

$$LCHG(i, j) = Cur(y,i, j) - BG(y,i, j) \qquad \textbf{(3)}$$

In the above formula, $Cur(y,i, j)$ represents the strength of signal Y of current frame at I, j column, $BG(y,i, j)$ 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 bellow.

$$\begin{aligned} CCHG(i, j) &= \left|(Cur(u,i, j) - BG(u,i, j)\right| \\ &+ \left|Cur(v,i, j) - BG(v,i, j)\right| \end{aligned} \qquad \textbf{(4)}$$

In the above formula, $Cur(u,i, j)$ and $Cur(v,i, j)$ denotes respectively the strength of signal U and Y of current frame at I, j column. $BG(u,i, j)$ and $BG(v,i, j)$ denotes respectively the strength of signal U and Y of current background frame.



(a) Image to be divided **(b) Brightness varigation** **(c) Color variation**

Figure 3 : Shadow detection

In Figure 3, Figure3 (a) is the image waiting for being detected, Figure 3 (b) is the variation LCHG of brightness at the white line in Figure 3 (a), Figure 3 (c) is the variation CCHG of color at the white line in Figure 3 (a). The range between the Vertical bars in Figure 3 (b) and Figure 3 (c) is the shadow region. From the Figure 3 (b), the image brightness in shadow region is reduced when LCHG<0, from Figure 3 (c), the variation of color is little.

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

(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≤LCHG≤THL2 and CCHG≤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.

As the 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.

The Figure 4 is the effect image after shadow elimination. MA2 is acquired by utilization of shadow elimination algorithm in the Figure 4 (a), from the Figure , there exist Isolated boundaries. MA3 is acquired by utilization of morphology in the Figure 4 (b), the noise and isolated boundaries are eliminated basically.

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 the height GH and width GW, and then calculate activity of each grid. The activity is defined as the following:

(a) Shadow elimination **(b) Shadow elimination processed**

Figure 4 : Shadow removal

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

$Active(x,y)$ denotes the activity of grid at x , y , $MA3(i,j)$ 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 8x8 grid. Figure 5 (b) utilizes boundary tracking algorithm to attain the initial contour.

(a) Activity grid **(b) Initial contour**

Figure 5 : Contour extraction

Contour approximation

After the initial contour is attained, algorithm of this paper utilizes active contour model to approach the True contour of moving object. Active contour model also called Snake model is 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. No more 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 set of collection of image, is denoted as:

$$V = \{v_1, v_2, \cdots, v_l\} \quad \textbf{(6)}$$

The total energy function of dynamic contour is defined as:

$$\begin{aligned} Esnake &= \sum_{i=1}^{l} E(v_i) \\ &= \sum_{i=1}^{l} \left[E_{\text{int}}(v_i) + E_{ext}(v_i) + E_{con}(v_i) \right] \end{aligned} \quad \textbf{(7)}$$

Where,

$$E_{\text{int}}(v_i) = \alpha E_{cnt}(v_i) + \beta Ecur(v_i) \quad \textbf{(8)}$$

$$E_{ext}(v_i) = \omega * Edge(v_i) \quad \textbf{(9)}$$

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

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 $Ecur$ denotes contour curvature. α and β are weighting constants. For open non-closed 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:

$$Edge(v_i) = -\left| \nabla f(v_i) \right|^2 \quad \textbf{(11)}$$

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 image. Because the initial contour extracted contains the objects to be split, energy constraint is devised to shrink 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:

$$Ei(v_i') = E_{\text{int}}(v_i') + E_{ext}(v_i') + Econ(v_i') \quad \textbf{(12)}$$

Select the lowest energy point as the current best position. For the first item $Ecnt$ of internal energy, its standardized form is as the following:

$$Ecnt(v_i) = \frac{\bar{d} - |v_i - v_{i-1}|}{\max_j \left\{ \bar{d} - |v_{ij} - v_{i-1}| \right\}} \quad \textbf{(13)}$$

In the above formula, $\{vij \mid j = 0,1,2,\cdots,8\}$ denotes the current contour point vi0 and its eight neighborhood points, $|vi - vi - 1|$ 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:

$$Ecur(v_i) = \frac{|v_{i-1} - 2v_i + v_{i+1}|^2}{\max_j \left\{ |v_{i-1} - 2v_{ij} + v_{i+1}|^2 \right\}} \quad \textbf{(14)}$$

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:

$$Eedge(v_i) = \frac{\min - \left|\nabla f(vi)\right|^2}{\max - \min} \tag{15}$$

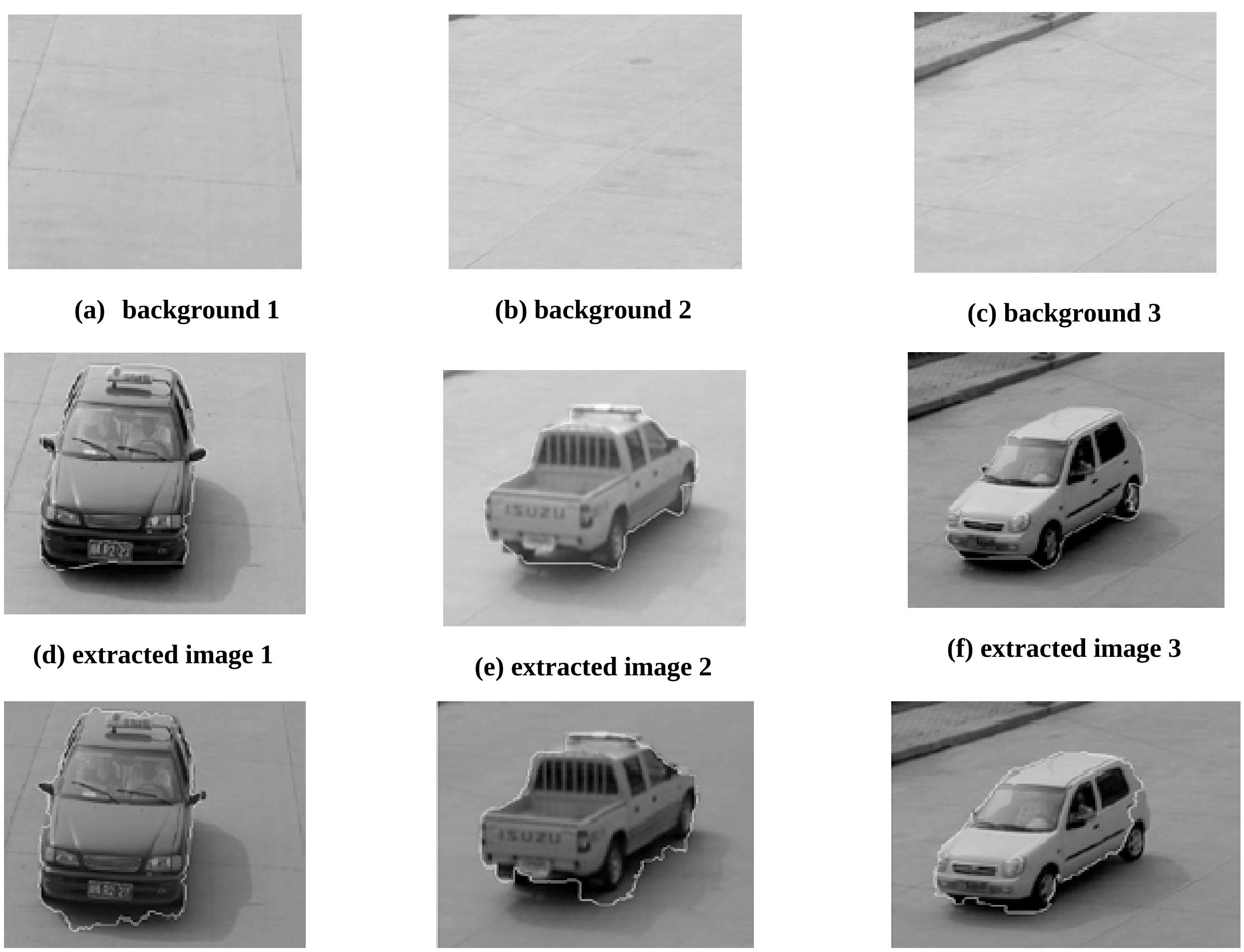
In the formula (15), max and min denote respectively the maximum and minimum gradient in the current field. Greedy algorithm can obtain quickly approximate optimal solution, whose complexity is only O (nm), in which n is the number of contour points in the active model, m is the number of iterations.

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. When the 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 not are able to reach the edge for the fracture edge employs the original greedy algorithm. The above improvement can be a good solution to the problem of excessive contraction.

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 constant 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 JPEG images collected which are decompressed do not need convert the time-consuming YUV color space to the HSV color space to operate. Moreover, in the elimination of shadows, it can effectively reduce the incompletion of shadow elimination or the excessive elimination probability to make the segmentation of target more accurate. Figure 6 is the effect of experimental comparison algorithm.



(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**

Figure 6 : Experiments

Figure 6 illustrates the experimental comparison employing the algorithm. Figure 6(a), 6(b) and 6(c) respectively are the background of Figure 6(d) and 6(g), Figure 6(e) and 6(h) and Figure 6(f) and 6(i). Figure 6(d) ~ (f) are the moving target employing the algorithm proposed in this paper, Figure 6(g) ~ (i) employs the HSV color space to extract the motion background. It can be seen from the Figure s, 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 is closed, 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 42F/S, which can reach real-time processing requirements.

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 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 can radiate the energy to the contour point, thus making contour point approach the complete object contour when the initial contour is incomplete.

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