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Moving Object Segmentation Based on Background Subtraction and Fuzzy Inference

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Abstract—**In order to improve the segmentation accuracy, reduce under-segmentation and over-segmentation, this paper proposes a new algorithm for detecting moving objects. The method is based on background subtraction algorithm and integrated with fuzzy inference for thresholding and background update. We use 7 fuzzy rules which can effectively model the membership of a pixel in a moving object during the fuzzy inference. The inference algorithm is both pixel-based and region-based. It properly segments the moving object from the stationary background. Moreover, the background model is updated by fuzzy logic with dynamic update rate over time to overcome the noise and illumination changes, which occurs frequently in complex natural environments. So the algorithm is suitable for a long run without losing accuracy. The experiment results show that our method is robust as well as fast in performance.**

Keywords-background subtraction; fuzzy;threshold.

I. INTRODUCTION

Video surveillance systems are widely used as low-level tasks of computer vision applications, such as video surveillance, robotics, authentication systems, and a pre-stage of MPEG4 image compression. There are three conventional approaches to moving object detection: background subtraction, temporal differencing and optical flow.

Background subtraction [1] - [3] may detects moving objects by subtracting estimated background models from images. This method is sensitive to illumination changes and small movement in the background, e.g. leaves of trees. The background subtraction system is used to provide moving object image through the threshold of difference images between the current image and reference background image. However, background subtraction is extremely sensitive to dynamic scene changes due to lighting and extraneous events. A common problem of background subtraction is that it requires a long time for estimating the background models [1].

Temporal differencing [4] - [5] makes use of the pixel-wise difference between two or three consecutive frames in video imagery to extract moving regions. It is a highly adaptive approach to dynamic scene changes; however, it fails in extracting all relevant pixels of a foreground object especially when the object has uniform texture or moves slowly [1].Instead, background subtraction provides the most complete feature data.

Optical flow[6] [7] can be used to detect independently moving objects in the presence of camera motion; however, most optical flow computation methods are computationally complex, and cannot be applied to full-frame video streams in real-time without specialized hardware[8]. Optical flow also has a problem caused by illumination changes since its approximate constraint equation basically ignores temporal illumination changes[1]

VSAM [8] have developed a hybrid algorithm [9] for detecting moving objects, by combining an adaptive background subtraction technique with a three-frame differencing algorithm.

Pal S K, King R A have developed a fuzzy thresholding through index of fuzziness algorithm [10] for detecting moving objects in 1983. Some authors have also used the idea of image fuzziness to develop new thresholding techniques [11].

II. PROPOSED METHOD

A. Overview

Distinguishing moving objects from the stationary background is both a significant and difficult research problem. The first step among almost all of the visual surveillance systems is detecting moving objects. Both create a focus of attention for higher processing levels such as tracking, classification and behavior understanding and reduce computation time considerably since only pixels belonging to foreground objects need to be dealt with.

The proposed method aims at extracting the moving objects in an input image from their background. The method is based on using background subtraction algorithm and fuzzy algorithm for separating moving objects from their background and update background model by fuzzy processing.

In this paper, for background subtraction algorithm, we make the following assumptions:

1) There exists a significant contrast between the moving objects and background;

2) Small moving object can be removed from segmentation results.

As depicted in Fig. 1, the proposed method consists of seven steps:

1) *Video sequence input*: read video frame from video input hardware device.
2) *Frame preprocessing*: video sequences global motion compensation and exposure compensation.
3) *Background subtraction*: describe in section "II-B".

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4) *Fuzzy inference*: describe in section "II-C".
5) *Background processing*: describe in section "II-D".
6) *Morphological processing*: the algorithm use "fill", "open" ,define the bounding box of moving area, and delete the small area object that less than give parameter .Then pass the results of fuzzy processing to "background processing model" .
7) *Segmentation result*: give the segmentation result.

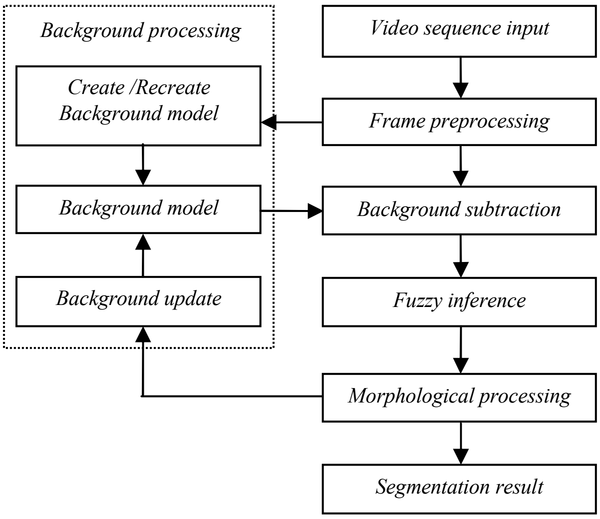


Figure 1. Overview of the proposed method.

B. Background Subtraction

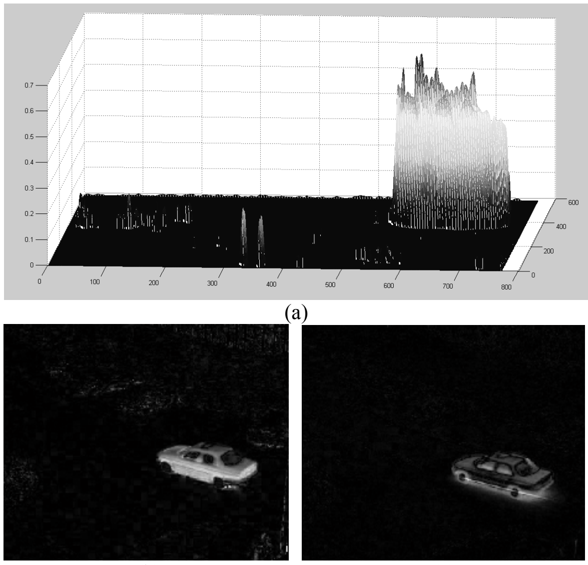
Conventionally, assuming that the background is stationary, then the moving object can be determined by taking the difference between the background image and the input image. Background subtraction finds moving objects information by subtracting background model from video sequence frame images.

In this paper, for gray video stream,only use intensity (lightness)signal. For color video stream, we can use HSI (hue-saturation-intensity) color space background model. The HSI system separates color information of an image from its intensity information,and has a good capability of representing the colors of human perception.

Considering a video stream from a stationary camera. Let $L_n(x,y)$ represent the lightness value at pixel position (x,y), at time t=*n*. $B_n(x,y)$ represent background model, $B_0(x,y)$ is initially setted to the first image. T is the threshold (described in section C).The background differencing rule suggests that a pixel is legitimately moving if its lightness has changed significantly between both the current image and the background. Conceptually, for gray video stream ,a pixel x is moving if

$$| L_n(x,y) - B_n(x,y) | > T \tag{1}$$

Fig. 2 shows a result of background subtraction for color video stream. After background subtraction (color or gray), the next step is fuzzy inference and thresholding, described in section II-C.



(b) (c)

Figure 2 Background subtraction In HSV color model：
(a) $| L_n(x) - B_n(x) |$. (b) Difference in hue. (c) Difference in lightness

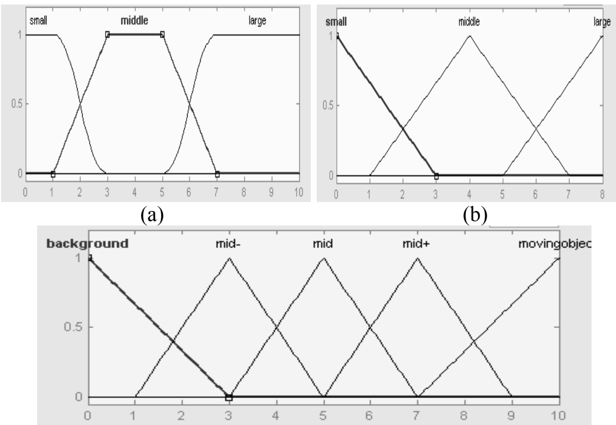
C. Fuzzy Inference

The foreground extraction problem is dealt with by change detection techniques, and thresholding techniques. In many cases, the threshold is selected empirically or by trial and error.

The major shortcoming of the single-threshold approach is that it often ends up with a foreground that is either oversegmented or undersegmented [2]. This comes as no surprise because the foreground and background pixels intertwined in the measurement space, which makes it impossible to have a global threshold that segments well. To alleviate the problem, it appears logical to instead of considering multiple thresholds or fuzzy techniques.

There are many (classical) thresholding techniques. The fuzzy set theory has attracted more and more attention in the area of image processing to develop new thresholding techniques. Fuzzy set theory provides a mechanism to represent and manipulate uncertainty and ambiguity.Fuzzy operators, properties, mathematics,and inference rules (IF-THEN rules) have found considerable applications in image segmentation. Despite the computational cost, fuzzy approaches perform as well as or better than their crisp counterparts. The most important advantage of a fuzzy methodology lies in that the fuzzy membership function provides a natural means to model the uncertainty in an image. Subsequently,fuzzy segmentation results can be utilized in feature extraction and object recognition phases of image processing and computer vision [11].

The proposed method use fuzzy inference method. Fig.3 shows the membership function of variables. The parameters of membership function are selected empirically or by trial. This algorithm is both pixel-based and region-based. The input variable "difference" is the background subtraction value at a pixel, scale range is 0-255, Fig.3 (a) only shown scale range 10/255. The input variable "area" is the count of pixels which is around and there is higher background difference value than the center pixel, scale range is 0-8.It is based on measurement of interpixel relations.



(a) (b)

(c)

Figure 3 Fuzzy inference memberships function: (a)Input variable "difference", S-function, Trapezium function, Z-function. (b) Input variable "area", Triangle function. (c) Output variable "object", Triangle function.

The list is the rules of the fuzzy inference:

1. If (difference is small) and (area is small) then (object is background)
2. If (difference is small) and (area is middle) then (object is mid−)
3. If (difference is small) and (area is large) then (object is mid)
4. If (difference is middle) and (area is small) then (object is mid)
5. If (difference is middle) and (area is middle) then (object is mid+)
6. If (difference is middle) and (area is large) then (object is moving object)
7. If (difference is large) then (object is moving object)

Fig. 4 shows the fuzzy inference surface.

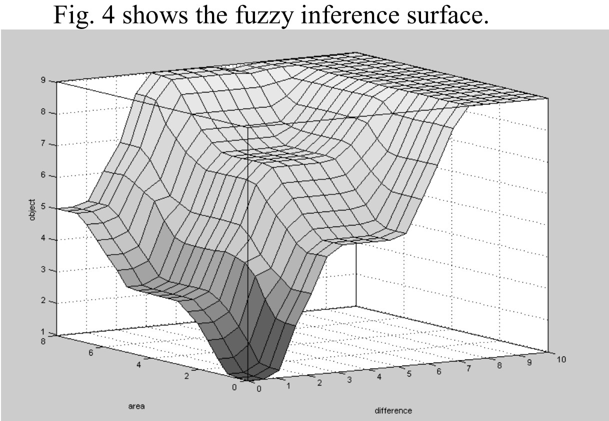


Figure 4. Fuzzy inference surface

The next step is thresholding. Let f represent the output value of fuzzy inference on pixel (x, y). $M(x,y)$ represent the thresholding segmentation result set. calculated by:

$$M(x, y) = \begin{cases} 1, & \text{if } f \ge 6 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

In morphological processing, method uses "open", "fill" and "label" operation, defines the bounding box of moving area, and delete the small area object that less than given parameter. Then pass the results to "background processing model" and give the segmentation result. Record the vertex coordinate of moving object bounding box, if the coordinate is not changed in 3 frames, then the moving object is a "ghost" object which moving object stop or a object start moving. For this condition, the propose method update background in the area of "ghost" object.

D. Background Processing

1) Create background model

The first background $B_0(x, y)$ is initially set to the first image (3) or average value of top *m* frames (4):

$$B_0(x,y) = L_0(x, y) \tag{3}$$

$$B_0(x, y) = \frac{1}{m}\sum_{k=1}^{m} L_k(x, y) \tag{4}$$

2) Recreate background model

Background model is sensitive from noise and illumination changes, which frequently occur in complex natural environments. Oversegmented or undersegmented will make the background model under updated or over updated. The proposed method will recreate background model (automatically or manually) when the result of segmentation is error.

3) Background update

Conceptually, by non-fuzzy method, the background $B(x,y)$ are updated over time as:

$$B_n(x,y) = \begin{cases} \alpha B_n(x,y) + (1-\alpha) L_n(x,y), & \text{x is non-moving} \\ B_n(x,y), & \text{x is moving} \end{cases} \tag{5}$$

Where α is a time constant that specifies how fast new information supplants old observations.

In this paper, the proposed algorithm use fuzzy method for background update, the α is given by S-function:

$$\alpha = \begin{cases} 0, & f \le 2 \\ 2((f-2)/4)^2, & 2 < f \le 4 \\ 1-2((f-6)/4)^2, & 4 < f < 6 \\ 1, & f \ge 6 \end{cases} \tag{6}$$

f represents the output value of fuzzy inference and morphological processing on pixel (x, y). Then the update function (5) changed to function (7):

$$B_n(x,y) = \alpha B_n(x,y) + (1-\alpha)L_n(x,y) \qquad (7)$$

The α is defined in (6). And the propose method update background in the area of "ghost" object, describe in section "II-C".Fuzzy update method can prevent under updated or over updated and make the segmentation robust.

III. EXPERIMENTAL RESULTS

A. Performance Evaluation

We tested our method on various video sequences, including cars (Fig. 5(a)), human being (Figs. 5(c),Fig. 5(e)). All sequences shown in Fig. 5 include several kinds of noise caused by illumination changes, small movement in the background and reflection. However, our results showed remarkable robustness against these environments. Our method succeeded detecting moving objects accurately in all video sequences in Fig. 5 for long time running. Fig. 5(b), 5(d) and 5(f) are the segmentation results.

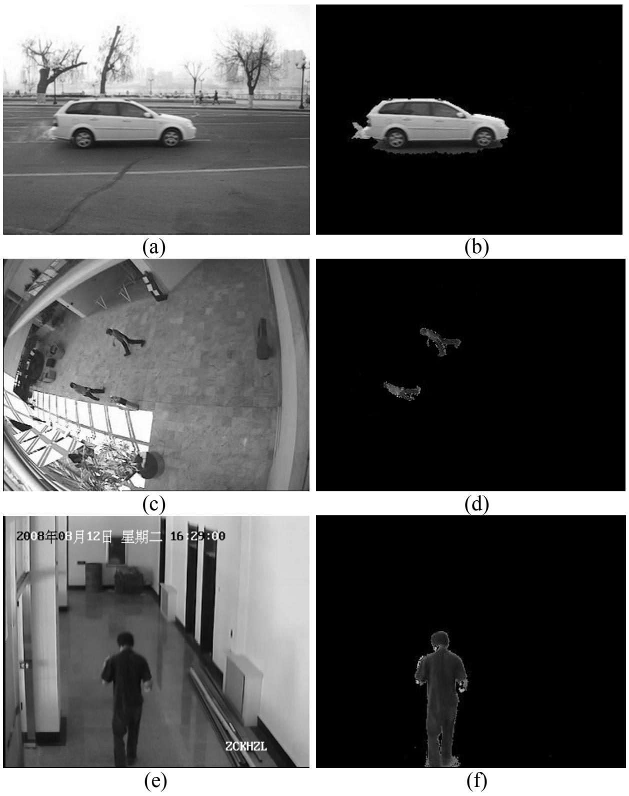


Figure 5 Segmentation results of propose method:
(a) Test frame car D61.
(b) Segmentation result of "(a)".
(c) Test frame Meet_WalkTogether1307.
(d) Segmentation result of "(c)"
(e) Test frame capture0200
(f) Segmentation result of "(e)"

B. Computational Cost

The computation of our system required average 0.08s/frame on Pentium4 2.0 GHz processor, use Matlab7.1 software, image size is 352*288 or 384*288. which satisfies requirement as a real-time system.

IV. CONCLUSION

In this paper, we introduce a real time and robust algorithm for detecting of moving objects. This method is based on background subtraction algorithm and uses fuzzy method both in thresholding and background update. Fuzzy inference can effectively reduce the over-segmentation and under-segmentation errors during the object extraction. In addition, dynamic background model re-creation by fuzzy logic enables our method to retain the segmentation accuracy over long time.

The experimental results show that our method is more accurate and robust than traditional background subtraction algorithms based on single threashold. It has good performance for real-time video surveillance applications.

REFERNCES

[1] Yi˘githan Dedeo˘glu, "Moving object detection tracking and classification for smart video surveillance,"[D]:[Ph D Thesis], Turkey, Bilkent university,August, 2004, pp.24-25

[2] Lu Wang and Nelson H. C. Yung, "Extraction of Moving Objects From Their Background Based on Multiple Adaptive Thresholds and Boundary Evaluation,"IEEE Transactions on intelligent transportation systems, vol.11, no.1, March 2010,pp.41-42.

[3] A.Neti, S.Colonnese, G.Russo,and P. Talone, "Automatic Moving Object and Background Separation,"[J].Signal Processing, 1998,2, 66 (2),pp.219-232.

[4] Alan J. Lipton, Hironobu Fujiyoshi,and Raju S. Patil. "Moving target classification and tracking from real-time video,"in Proc. IEEE Workshop on Applications of Computer Vision, Princeton, NJ, 1998,pp.8-14

[5] Anderson C, Burt P,and Van der Wal G. "Change detection and tracking using pyramids transformation techniques," in Proc.SPIE Conference on Intelligent Robots and Computer Vision, Cambridge, MA,USA:[s.n.], vol 579,1985, pp.72-78

[6] A.Murat Tekalp. "Digital Video Processing,"Prentice Hall,Inc.1996,pp.94.

[7] H.Gharavi,M.Mills. "Block-Matching Motion Estimation Algorithms New Results," proc.IEEE Transactions.Circuits and Systems,vol.37, no 5,pp 649-651,May 1990.

[8] Robert T. Collins, Alan J. Lipton, Takeo Kanade, Hironobu Fujiyoshi, David Duggins, Yanghai Tsin,et al. "A system for video surveillance and monitoring,"VSAM final report[R].CMU-RI-TR-00-12, Carnegie Melon University, Pittsburgh,Peen, America, 2000.

[9] Xiao Li-jun, Yu Zhe-zhou,Zhou Xu,Zheng Shang,Li Hai-feng, "Moving Object segmentation based on symmetrical differencing algotithm in video sequences,"Journal of JiLin University(Science Edition),Vol.46, No.4, pp.691-696,July 2008.

[10] Pal S K, King R A , Hashim A A. "Automatic graylevel thresholding through index of fuzziness ent ropy". Pat tern Recognit ion Let ters , 1983 , 1 pp:141-146.

[11] Orlando J. Tobias, Rui Seara, "Image Segmentation by Histogram Thresholding Using Fuzzy Sets,"in Proc.IEEE Transactions on image processing,vol.11, no.12, pp.1457-1465,Dec.2002.