ICSP2008 Proceedings

A Novel Fuzzy Background Subtraction Method Based on Cellular Automata for Urban Traffic Applications

Moein Shakeri[1], Hossein Deldari[1], Homa Foroughi[1], Alireza Saberi[2], Aabed Naseri[2]
[1]*Department of Computer Engineering, Ferdowsi University of Mashhad, Iran*
[2]*Department of Electrical and Computer Engineering, Concordia University, Canada*
mo_sh88@stu-mail.um.ac.ir,hd@um.ac.ir, ho_fo46@stu-mail.um.ac.ir,
saberi_alireza@ece.concordia.ca, anaseri1@ece.concordia.ca

Abstract

Computational structure of cellular automata has attracted researchers and vastly been used in various fields of science. They are especially suitable for modeling natural systems that can be described as massive collections of simple objects interacting locally with each other, such as motion detection in image processing. On the other hand, extraction of moving objects from an image sequence is a fundamental problem in dynamic image analysis Nowadays background modeling and subtraction algorithms are commonly used in real-time urban traffic applications for detecting and tracking vehicles and monitoring streets. In this paper by the use of cellular automata, a novel fuzzy approach for background subtraction with a particular interest to the problem of vehicle detection is presented. Our experimental results demonstrate that fuzzy-cellular system is much more efficient, robust and accurate than classical approaches.

1. Introduction

Background extraction is an important part of moving object detection algorithms that are very useful in surveillance systems. Method of background extraction during training sequence and updating it during input frame sequence is called background modeling. There are various methods for background modeling. Some of these methods such as mean filter [3] and median filter [4] need very huge memory capacity and some other such as Eigen-background [5] and Mixture of Gaussian (MOG) [6,7] have more computational complexity. According to importance of real-time computations in the surveillance systems, improvement the efficiency of simple background subtraction methods is so significant. To this end, in this paper we propose a novel fuzzy method based on computational model of cellular automata for background subtraction and moving object detection. Our experimental results demonstrate that the fuzzy-cellular system is much more efficient, robust and accurate than classical approaches.

978-1-4244-2179-4/08/$25.00 ©2008 IEEE

1.1. Cellular Automata

Cellular Automata (CA) are a class of discrete dynamical systems, consisting of an array of nodes (cells) of some dimension, n. Each cell can be in one of *k* different states at a given tick of the clock. CA provides a useful mathematical model of massively parallel multi-processor systems. Each cell can be considered a processor, with the cell states corresponding to the finite possible states of the processor. The processors in the neighborhood of a given processor, *P*, are the processors directly connected to *P*. The above could also be describing a neural net, with 'neuron' in place of 'processor'. How to get such a system to perform useful computational tasks, making optimal use of all that parallel computing power, is a central problem in computer science [1].

2. Background Subtraction

Identifying moving objects from a video sequence is a fundamental and critical task in video surveillance, traffic monitoring and analysis, human detection and tracking. A common approach to identifying the moving objects is background subtraction, where each video frame is compared against a reference or background model. Pixels in the current frame that deviate significantly from the background are considered to be moving objects. These foreground pixels are further processed for object localization and tracking.

2.1. Standard Background Subtraction

When the background image obtained, moving objects of the scene can be detected using background subtraction. The simplest and fastest background modeling technique, frame differencing uses the video frame at time *t-1* as the background model for the frame at time t. By applying a threshold on absolute difference of current image frame and background image, moving objects can be detected.

$$BGS(i,j)=\begin{cases}1 & if\left|I_t(i,j)-BG_{t-1}(i,j)\right|>th_s\\ 0 & otherwise\end{cases} \quad (1)$$

In this equation, I_t is input frame at time *t*, BG_{t-1} is background image at time *t-1* and *BGS* is the result. In standard background subtraction method a hard limiter function is used to determine a pixel is a moving object pixel or no. to improve the efficiency a fuzzy method was proposed in [2] that used saturating linear function instead of hard limiter:

$$FBGS(i,j)=\begin{cases}1 & if\left|I_t(i,j)-BG_t(i,j)\right|>th_s\\ \dfrac{\left|I_t(i,j)-BG_t(i,j)\right|}{th_s} & otherwise\end{cases} \quad (2)$$

Since the background subtraction output must be 1 or 0 and the result of *FBGS* is a real value in range *[0,1]*, a low pass filter is used for binarization. Therefore, final output can computed as follows:

$$BGS(i,j)=\begin{cases}1 & if\left|LPF(FBGS(i,j))\right|>th_{fs}\\ 0 & otherwise\end{cases} \quad (3)$$

Where, the th_{fs} is a threshold that determines background subtraction was performed or not.

2.2. Running Average

The commonly, fastest and the most memory compact background modeling is running average method. In this method, background extraction is done by arithmetic averaging on train sequence. Because of scene illumination changes background image must be updated in each frame:

$$BG_t=\alpha.BG_{t-1}+(1-\alpha).I_t \quad (4)$$

In this equation α must be in range *(0,1)*. A modified running average method for background updating is as follows:

$$BG_t=\begin{cases}\alpha.BG_{t-1}+(1-\alpha).I_t & if\left|I_t(i,j)-BG_{t-1}(i,j)\right|\\ BG_{t-1} & otherwise\end{cases} \quad (5)$$

Where th_u is update threshold and must be less than or equal with th_s. Fuzzy theory can also be used in running average method to update background image. In fuzzy running average method, *α* is not an overall value. It is defined for each pixel based on current value of fuzzy background subtraction. In [2] the following equation is used to compute value of α in each pixel:

$$\alpha(i,j)=1-(1-\alpha_{\min})\exp(-5*FBGS(i,j)) \quad (6)$$

Where α_{min} is the minimum value for α. According to [2] for real-time computation it is better to implement α as a look-up table. So background updating in a given pixel using fuzzy background subtraction will be defined as:

$$BG_t(i,j)=\alpha(i,j).BG_{t-1}(i,j)+(1-\alpha).I_t(i,j) \quad (7)$$

2.3. Drawbacks of Fuzzy Background Subtraction Method

One of the drawbacks of fuzzy background subtraction method is the threshold value that's estimated by trial and error [2]. Because of performing trial and error procedure at each frame, the detection time would be increased. Besides, illogical determination of threshold value, results in erroneous moving object detection. Furthermore, detection of moving objects that their gray level is similar to background gray level isn't done accurately. This problem is occurred because of using a predefined threshold value for the entire image. Whereas, at each step of CA computations, a specific threshold is defined regarding to kind of neighbors.

3. Fuzzy-Cellular Proposed Method

In our proposed method, fuzzy background subtraction is done by using cellular automata. If each frame sequence is considered as a 2D cellular space, then each pixel will be regarded as a cell of cellular automata. Based on this assumption, each frame sequence can be modeled by a cellular automata and specific cellular automata rules can be applied on pixels. Regarding inherent characteristics of cellular automata, computation are done independently and concurrently in all of cells.

3.1. Proposed Background Subtraction Method

To overcome reported challenges in this paper we propose a novel fuzzy-cellular background subtraction method. Instead of using trial and error procedure, our approach utilizes a specific threshold value that's obtained from below equation:

$$cell(i,j)=\begin{cases}1 & if\ \dfrac{|I_t(i,j)-BG_{t-1}(i,j)|}{255}>e^{-(3+m)/2}*k\\ 0 & otherwise\end{cases} \quad (8)$$

Where I_t is the input frame at time *t* and BG_{t-1} is the background image at time *t-1*. Note that dividing the difference of input and background frames on 255, gives a number in range *[0,1]*. In this equation *m* indicates number of steps that background subtraction procedure has been performed on this frame. Also *k* is obtained by using fuzzy sets. The final output *cell(i,j)* shows active and non-active cells of each frame. It must be taken into consideration that initial values of m and k are set to 0 and 1. In figure 1, N shows number of active cells respect to all of block cells. These fuzzy sets are obtained regarding to number of the active cells in the purposed block, e.g *Low* linguistic term is 1 only in range [0,0.25].

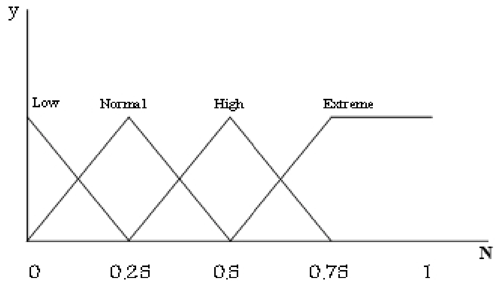

Figure 1 Fuzzy Sets for Determining Value of k

3.2. Proposed Running Average Method

In order to have higher recognition rate a novel fuzzy-cellular running average method is proposed. In the proposed approach the following equation is used for determining effect of current and previous frames:

$$\alpha(i,j)= 1-0.1*\exp(-5*cell(i,j)) \quad (9)$$

By using α, fuzzy-cellular background subtraction will be defined as follows:

$$BG_t(i,j)=\alpha(i,j)*BG_{t-1}+(1-\alpha(i,j))*I_t(i,j) \quad (10)$$

3.3. Fuzzy Rules for Determining Value of k

To detect value of k, firstly number of active cells of the purposed block is obtained and then according to the interval that N belongs to it, following fuzzy rules are used:

Table 1 Fuzzy Rules for Detecting k

Rule 1	*If N is Normal or High then* $f_1=1$
Rule 2	*If N is Low then* $f_2=A_1*y_{12}$
Rule 3	*If N is Extreme then* $f_3=A_2*y_{11}$

Where A_1 and A_2 are constants and set to 0.5 and 2. And then by applying below deffuzifier, value of k is determined.

$$k = \sum_{i=1}^{3} Fi \Big/ n \quad (11)$$

Where n is the number of rules that have a non-zero output. Now to determine moving object existence in a detection region, we use the following rule:

If [*Sum (cell) < 0.4 * i*j*] & [$k * e^{-(3+m)/2} > 0.03$] Then
$I_t(i,j)= 0.2 * (I_t(i-1,j)+ I_t(i,j+1)+ I_t(i,j-1)+ I_t(i+1,j)+ I_t(i,j))$
Repeat again
Elseif [*Sum (cell) < 0.4 * i*j*] & [$k * e^{-(3+m)/2} > 0.03$] Then
Moving Object Detected
Else
No Moving Object Detected

According to the above rules, if purposed cells don't recognized as foreground, then mean value of cell and its four neighbors is calculated and replaced by value of under computation cell in the frame and all of these tasks are repeated again. Before repeating the operation on the current frame all of active cell are reset and reinitialized using equation 10. Repetition these operations yield the minimum value of threshold for the purposed frame. Finally if no moving object is detect in the block, we can decide that there's no moving object in the scene.

4. Vehicle Detection Using Fuzzy-Cellular Background Modeling

One of important applications of background modeling is in Vehicle Detection Systems (VDS). VDSs have to process input frame sequence in real-time usually on a general-purpose processor. Generally, VDSs [8-10] use background modeling and subtraction techniques to detect vehicles, because the other techniques have more computational complexity. Our proposed algorithm for vehicle detection is based on trip-line approach. In trip-line approach, some rectangular regions are selected on image as detection regions. Trip-line approach has lower computational complexity with respect to other approach that process the entire image frame. Usually, detection region is a rectangle that its size is equal with size of vehicle image.

5. Experimental Results

To compare our proposed fuzzy-cellular method with classic and fuzzy approaches [2], the application of these methods in vehicle detection is used. In our experiment space three different moving objects have been selected:

1. Moving objects that their gray level is totally different from background gray level: both fuzzy [2] and fuzzy-cellular methods are able to detect the vehicle. The rightmost column of figure 2 is related to this type of vehicles.
2. Moving objects that their gray level is a little different from background gray level: classic approach cannot detect the moving object properly, however the fuzzy [2] and fuzzy-cellular approaches, detect the vehicle correctly. The middle column of figure 2 has dedicated to this type of vehicles.
3. Moving objects that their gray level is entirely similar to background gray level: none of the classic

and fuzzy [2] methods are able to detect the vehicle. Whereas our fuzzy-cellular approach detects the moving object accurately. The leftmost column of figure 2 demonstrates this type of vehicles.

Note that in figure 2, in each column figures 2(a), 2(b) and 2(c) show results of classic, fuzzy [2], and fuzzy-cellular background subtraction methods respectively.

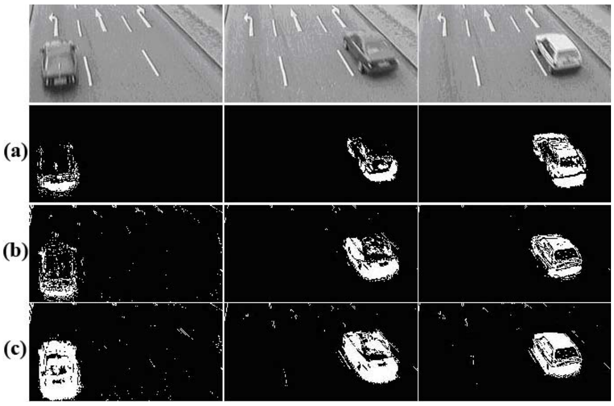

Figure 2 Result of Vehicle Detection Using (a)Classic Background Subtraction (b) Fuzzy Background Subtraction (c) Fuzzy-Cellular Background Subtraction

To evaluate vehicle detection system, we used False Detection Rate (FDR) and False Rejection Rate (FRR). FDR shows the false detection error rate that system detects a vehicle in an empty region. FRR shows the false rejection error rate that system does not detect the vehicle in an occupied region.

Table2 Error Rate

	FDR	FRR	Error Rate
Vehicle Detection	4%	19%	23%
Fuzzy Approach	5%	12%	17%
Fuzzy – Cellular Approach	3%	5%	8%

Experimental results show that FDR and FRR of fuzzy-cellular vehicle detection are 3% and 5%. It shows total error rate of proposed fuzzy-cellular VDS is 9% and 15% lower than classic and fuzzy [2] VDS respectively.

6. Conclusions

In this paper some weaknesses of classic and fuzzy running average method for background modeling and background subtraction is studied. To overcome existent challenges we propose a novel fuzzy-cellular method for background subtraction and moving object. One dominant note in this paper is that instead of trial and error procedure we use cellular automata to determine optimal value of threshold. Our system is able to detect all of moving objects available in the scène. This significant advantage is due to cellular automata inherent characteristics. Indeed at each step, the threshold valued is determined according to number of active cells, so moving objects that their gray level is entirely similar to background gray level are simply detected.

References

[1] N.Ganguly, B.K. Sikdar, A.Deutsch , G. Canright, P.P. Chaudhuri, “A Survey on Cellular Automata” , 2003.

[2] M.H Sigari, “Fuzzy Running Average and Fuzzy Background Subtraction: Concepts and Application” , IJCSNS International Journal of Computer Science and Network Security , Vol.8, No.2, February 2008.

[3] B. P. L. Lo and S. A. Velastin, "Automatic congestion detection system for underground platforms", International Symposium on Intelligent Multimedia, Video and Speech Processing, pp. 158-161, 2000.

[4] R. Cucchiara, C. Grana, M. Piccardi, and A. Prati, "Detecting moving objects, ghosts and shadows in videostreams", IEEE Transaction on Pattern Analysis andMachine Intelligence, vol. 25, no. 10, pp. 1337-1342, 2003.

[5] N. M. Oliver, B. Rosario, and A. P. Pentland, "A Bayesian Computer Vision System for Modeling Human Interactions", IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 22, no. 8, pp. 831-843, 2000.

[6] C. Stauffer, W. E. L. Grimson, "Adaptive background mixture models for real-time tracking", IEEE International Conference on Computer Vision and Pattern Recognition (CVPR), pp. 246-252, 1999.

[7] W. T. Dong, Y. S. Soh, "Image-based fraud detection in automatic teller machine", International Journal of Computer Science and Network Security (IJCSNS), vol. 6, no. 11, November 2006.

[8] M. Yu, Y. D. Kim, "Vision based vehicle detection and traffic parameter extraction", IEICE Transaction on Fundamental Electronic, Communication and Computer Science, vol. E84-A, no. 6, pp. 1461-1470, 2001.

[9] O. Achler, M. M Trivedi, "Camera based vehicle detection, tracking, and wheel baseline estimation approach", the 7th International IEEE Conference on Intelligent Transportation Systems, pp. 743-748, October 2004.

[10] B. Coifman, D. Beymer, P. McLauchlan, J. Malik. "A realtime computer vision system for vehicle tracking and traffic surveillance", Trasportation Research: Part C, vol. 6, no. 4, pp. 271-288, 1998. IJCSNS International Journal of Computer Science and Network Security, VOL.8 No.2, February 2008