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AN INNOVATIVE TECHNIQUE FOR SEGMENTATION OF FOREGROUND OBJECT IN VIDEO

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ABSTRACT

Locating moving objects in a video sequence is the first step of many computer vision applications. Many different methods have been proposed over recent years. Among the various motion detection techniques, background subtraction methods are common, especially for application relying on fixed camera. In this paper we present an innovative technique for motion detection which compares current pixel value with the set of pixel values taken in the past to find whether that pixel belongs to the background or not and thereby foreground object can be extracted and our work shows good results when compared to other techniques.

KEYWORDS: Background Subtraction (BS), Computer Vision, Image Segmentation, Pixel Classification, Video Signal Processing

INTRODUCTION

Background Subtraction (BS) is widely used approach for detecting moving objects of interest in videos in diverse applications including remote sensing, surveillance, medical diagnosis and underwater sensing. As a basic, the background must be a representation of the scene with no moving objects and must be kept regularly updated so as to adapt the varying luminance conditions and geometry settings.

Several approaches are available to detect, segment and track objects automatically in videos. Simple motion detection algorithms compare a static background with the current frame of a video scene pixel by pixel. The idea behind BS is to build a background model and compares this model with current frame to detect area where significant difference occurs. Therefore the aim of the Background Subtraction is to distinguish moving object(s) (foreground object) from background. In real life scenarios background may contain static objects, slow moving objects such as waves on the water, trees shaken by the wind etc. Also when static object starts moving, background subtraction algorithm detects the object in motion. For short video sequences and indoor sequences, static background model might be appropriate, but the model is ineffective for most of the practical situations. In this paper we present an idea for motion detection which compares current pixel value with the stored set of pixel values taken in the past to find whether that pixel belongs to the background or not in a video scene and thereby extracting the foreground region.

PREVIOUS RESARCH

Most BS techniques share a common framework: they make the hypothesis that the observed video sequence I_s, is made up of a fixed background B in front of which moving objects are observed. With the assumption that a moving object at a time has a colour different from the one observed in B, the principle of BS method can be explained by

$$X_t(s) = \begin{cases} 1 & \text{if } d\,({}_{I_{s,t}}, B_s) > \tau \\ 0 & \text{otherwise} \end{cases}$$

Where Xt(s) is the motion label field at time t, d is distance between Is,t the video frame at time t at pixels and Bs the background t pixel s, τ is threshold.

The main difference between most BS methods is how B is modeled, how does it behave, how is the model initialized and how is updated over time. The approaches reviewed in this paper range from simple technique to more sophisticated and complex technique aiming to achieve the highest possible results under any possible circumstances. The authors [1] described the background with a gray scale / color image B. Foreground detection is described in [2] is a comparison process involves the comparison of observed image with an estimated image that does not contain any object of interest and this process divides the observed image into two complementary sets of pixels that cover the entire image:

- the foreground that contains the objects of interest, and
- the background, its complementary set

Many background subtraction techniques have been proposed with as many models and segmentation strategies. According to [3], a background subtraction technique must adapt to gradual or fast illumination changes (changing time of day, clouds, etc), motion changes (camera oscillations), high frequency background objects (e.g., tree leave or branches), and changes in the background geometry (e.g., parked cars).The method described by Seiki *et al.* in [4] is based upon the assumption that neighboring blocks of background pixels should follow similar variations over time. While this assumption holds most of the time, especially for pixels belonging to the same background object, it becomes problematic for neighboring pixels located at the border of multiple background objects. A solution to this problem is PCA and in [5] authors discussed on PCA reconstruction error. Independent Component Analysis (ICA) of serialized images from a training sequence is described in [6] in the training of an ICA model which is robust to indoor illumination changes.

In [7] authors proposed a spatio-temporal saliency algorithm especially for highly dynamic backgrounds. By constantly updating the model parameters, Pixel-based background subtraction techniques [8,9] compensate the lack of spatial consistency. A method for properly initializing a Gaussian background model from a video sequence in which moving objects are present is proposed in [10]. In [11]Stauffer and Grimson discussed the most popular pixel level algorithm named as Gaussian Mixture Model (GMM) in which the distribution of each pixel value over time as a Mixture of Gaussians (MoG), which is adaptively updated in an online manner, and then classify incoming pixels into either background or not.

PROPOSED METHOD

Let p(x) be the value in Euclidean color space taken by the pixel at location x in a frame and B(x) be the background model for each background pixel x which is defined by a sphere having radius R with p(x) as center. Neglecting time parameter, B(x) is modeled with **n** background samples taken in the previous frames.

$$B(x) = [B_1, B_2, B_3, \ldots B_n]$$

In our Background Subtraction problem, to classify a new or current pixel value, it has to be compared with set of background sample values taken in the past instead of doing comparison with a single pixel value. The flowchart of the proposed method is shown in figure 1.

To classify a pixel value p(x),

Step 1: p(x) has to be compared with B(x) which is defined by a sphere having radius R with p(x) as center.

Step 2: Find the intersection value of p(x) with B(x) which involves distance calculation between p(x) and model samples B_1 to B_n individually.

Step 3: If the result of intersection is greater than or equal to predefined threshold value, then p(x) is classified as background pixel. Otherwise it is classified as foreground sample value.

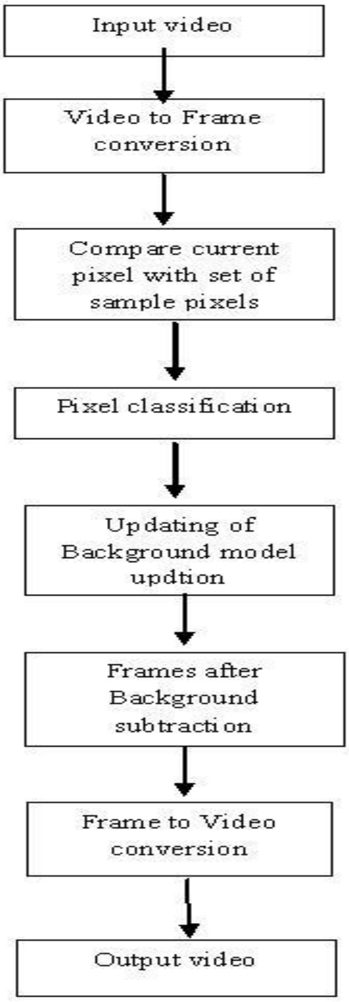


Figure 1: Flowchart of Our Proposed Method

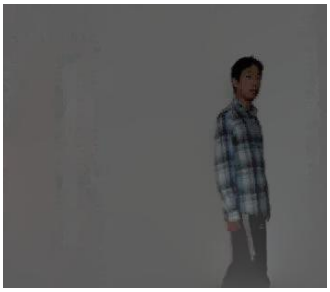
Background model has to be updated continuously to cope up with the changes in the lighting conditions and to handle new objects coming into the scene. We discard the sample randomly according to a uniform probability density function to overcome the drawbacks in blind update policy. So our model contains samples from the recent past but older samples should not necessarily be discarded.

EXPERIMENTAL RESULTS

In this section we are comparing the results of our proposed method with other two methods namely Approximate Median method and Mixture of Guassian.

For our comparison we used two video sequences namely man and san_fran_traffic_30sec_QVGA_Cinepak. Comparative background subtraction for one frame (frame number 53) from man sequence and from san_fran_traffic_30sec_QVGA_Cinepak sequence is shown in figure 2 and figure 3 respectively. From our observation, when we compare the results of Our method with Approximate Median method and Mixture of Guassian method Our method produces clear and noiseless output.

(a) (b)



(c) (d)

Figure 2: Comparation of Background Subtracted Image Obtained from Three Different Techniques Taken from Man Sequence (a) Input Image (b) Approximate Median (c) Mixture of Guassian (d) Our Method

(a) (b)

(c) (d)

Figure 3: Comparation of Background Subtracted Image Obtained from Three Different Techniques Taken from san_fran_traffic_30sec_QVGA_Cinepak Sequence (a) Input Image (b) Approximate Median (c) Mixture of Guassian (d) Our Method

CONCLUSIONS

The key element which makes this system robust is the classification model which is based upon the correlation between current or new pixel and the corresponding background pixel model. Another important key element is updating model in which instead of removing older values first, pixel values are replaced randomly according to uniform probability density function. We then compared our method to other methods with two video sequences. For real time applications we may need a fast high performance system on the other hand offline applications we may use a relatively cheap (and slower in performance). It can also be seen from the diverse nature of the techniques used that the field has a lot of room for improvement.

REFERENCES

1. Q. Zhou and J. Aggarwal. Tracking and classifying moving objects from video. *in IEEE Proc. PETS Workshop*, 2001.
2. A.Mclvor, "Background subtraction techniques," in Proc. Image Vis Comput., Auckland, NewZealand, Nov.2000
3. M. Piccardi, "Background subtraction techniques: A review," in *Proc. IEEE Int. Conf. Syst., Man Cybern.*, The Hague, The Netherlands, Oct. 2004, vol. 4, pp. 3099–3104.
4. M. Seki, T. Wada, H. Fujiwara, and K. Sumi, "Background subtraction based on cooccurrence of image variations," in *Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit.*, Los Alamitos, CA, Jun. 2003, vol. 2, pp. 65–72.
5. N. Oliver, B. Rosario, and A. Pentland, "A Bayesian computer vision system for modeling human interactions," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 22, no. 8, pp. 831–843, Aug. 2000.
6. D.-M. Tsai and S.-C. Lai, "Independent component analysis-based background subtraction for indoor surveillance," *IEEE Trans. Image Process.*, vol. 18, no. 1, pp. 158–167, Jan. 2009.
7. V. Mahadevan and N. Vasconcelos, "Spatiotemporal saliency in dynamic scenes," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 1, pp. 171–177, Jan. 2010. 465–475.
8. A. El Maadi and X. Maldague, "Outdoor infrared video surveillance: A novel dynamic technique for the subtraction of a changing background of IR images," *Infrared Phys. Technol.*, vol. 49, pp. 261–265, Jan. 2007.
9. R. Abbott and L. Williams, "Multiple target tracking with lazy background subtraction and connected components analysis," *Mach. Vis. Appl.*, vol. 20, pp. 93– 101, Feb. 2009.
10. D. Gutchess, M. Trajkovics, E. Cohen-Solal, D. Lyons, and A. Jain, "A background model initialization algorithm for video surveillance," in *Proc. Int. Conf. Comput. Vis.*, Vancouver, BC, Jul. 2001, vol. 1, pp. 733–740.
11. C. Stauffer and E. Grimson, "Adaptive background mixture models for real-time tracking," in *Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit.*, Ft. Collins, CO, Jun. 1999, vol. 2, pp. 246–252.
12. O.Barnich and M. Van Droogenbroeck, "ViBe: A powerful random technique to estimate the background in video sequences," in *Proc. Int. Conf. Acoust., Speech Signal Process.*, Apr. 2009, pp. 945–948.