Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X
IMPACT FACTOR: 5.258

IJCSMC, Vol. 5, Issue. 3, March 2016, pg.705 – 709

BACKGROUND MODELS FOR TRACKING OBJECTS UNDER WATER

Susmetha KC[1], Mrs. Kavitha KK[2]

BE Information Science and Engineering, New Horizon College of Engineering, Bangalore, India[1]
Asst. Professor, Dept. Of Information Science and Engineering, New Horizon College Of Engineering, Bangalore, India[2]
7259264939, sushmithakundanam@gmail.com

ABSTRACT: This paper presents a novel background analysis technique to enable robust tracking of objects in water- based scenarios. We present a new method for object tracking using background subtraction. This is a effective method in which the background is captured in advance without the presence of the object. Once the object enters the area, the image along with the object is captured. These two images are compared, and background is eliminated. The proposed AdaDGS method can apply well to this task. The moving Object is tracked and the Background region is subtracted. Object Alone will be present after the background subtraction. This method works well in highly textured environments and ideal for real applications.

INTRODUCTION

The ability to reliably separate intensity changes due to temporal background variation from those due to foreground objects entering the field of view is essential for subsequent object extraction and

tracking [1]. Moving object detection is not only useful for object tracking for any visual system, it is also the first step of many image Processing applications, for example video indexing and human machine Interaction.

Background subtraction segments foreground objects more accurately in most cases compared to other common moving object detection methods, and detect foreground objects even if they are motionless [2]. However, one drawback of traditional background subtraction methods is that they are susceptible to environmental changes, for example, gradual or sudden illumination changes. The reason for this drawback is that most methods assume a static background, and hence one needs to update the background model for dynamic backgrounds [3]. The update of the background model is one of the major challenges for background subtraction methods.

Another contribution of this paper is to introduce a method to detect sudden illumination changes and segment moving objects during these changes [4]. Sudden illumination change is still a very challenging problem for foreground segmentation as background dynamics varies frequently. Some examples of sudden illumination changes are turning on/off light sources in a room, or open/close window curtains or doors. These situations alter the background model and make the color or intensity-based subtraction methods fail (false positive i.e. detecting background pixels as foreground pixels).

We propose an effective scheme for updating the background and adaptively model dynamic scenes. Unlike the traditional methods that use the same learning rate for the entire frame or sequence [5], our method assigns a learning rate for each pixel using two parameters. The first parameter depends on the difference between the pixel intensities of the background model and the current frame. The second parameter depends on the duration of the pixel being classified as a background pixel.

RELATED WORK

Selective Averaging Method

In this method we firstly construct a background model in the absence of the object using selective averaging method. Once the background is captured and the object enters this region of background, these two images are subtracted. This is called background subtraction. Finally, background model is updated foe every frame in order to accommodate the background dynamics such as waving tree leaves and illumination changes [1].

Mixture of Adaptive Gaussians

In this method we model the values of a particular pixel as a mixture of Gaussians, rather than explicitly modelling the values of all the pixels as one particular type of distribution. Based on the persistence and the variance of each of the Gaussians may correspond to background colors. This system adapts to deal robustly with lightning changes, slow moving objects, and repetitive motions of scene elements. If only lightning changed over time, Single Gaussian per pixel would be sufficient, but multiple surfaces often appear in the view of a particular pixel and lightning conditions changes. Therefore we use mixture of Adaptive Gaussians to approximate the process [2].

RGB Background Modelling Method

Moving object detection involves two stages. One is extraction stage based on color background modelling i.e. morphological operations, RGB background modelling and second stage is grouping of moving objects which is based on blob labelling. Extraction of moving regions from sequential images is carried out by using gray level background modelling but in this process there is loss of image information as compared to color background modelling. Therefore we make use of RGB background modelling method that prevents excessive loss of information also takes less computational time [3].

Structural Background Model

Technique is to develop a background model that is a combination of statistical and structural analysis to handle the changes in the background. The input frame first passes through the per-pixel statistical model which produces the first foreground map. The value results in a large number of foreground moving regions (a motion map). The output of motion map filter serves as a domain for localized optical flow calculations. For each motion map region we compute the coherence of the optical flow in that region. The result of which is the second foreground map. The structural background model is a fusion of these two maps i.e. we combine a statistical background model with optical flow calculations to develop the structural background model [4].

Linear Spatial Filter

Consider, let I(t) be a frame at time t, and I(t+1) is a frame at time t+1 in a video sequence. In order to identify the objects to be tracked from the sequence we start subtracting the common background in a frame i.e. $E(t) = | I(t) – I(t+1) |$.
If the two frames are same, then the value of E(t) will be zero, which means there is no displacement of the object between the frames. Otherwise, the value is the value of the pixel position at the place of the object in the frame or pixel positions that have moved. We have to remove the pixel motion registered in E(t) due to noise and intensity changes. These changes have high frequency content in them, and can be solved using Gaussian frequency domain low ass filter which is also known as linear spatial filter. The filter averages the pixel in the frame mask and the value of every pixel in the image is replaced b the average of a group levels defined by the mask. This process gives an image with reduced sharp transitions in the gray levels [5].

PROPOSED SYSTEM

To detect the moving objects using background subtraction, the basic step is to construct the background model at the beginning of a video sequence. We assume that the sequence starts with the background in the absence of moving objects.

After obtaining the background model, we need to obtain the difference between the current frame and the background model. This is called background subtraction. This is achieved using AdaDGs (Adaptive Dynamic Group Sparsity) method. This method is mainly used to remove noise that is caused by waves or any other moving vessels.

CONCLUSION

In this paper we have proposed a new approach for background subtraction. In contrast to the traditional background subtraction techniques, our method can converge to the current background dynamics more rapidly and accurately. With the AdaDGS (Adaptive Dynamic Group Sparsity) model, it is very robust to illumination changes. Our proposed algorithm effectively removes noise thereby increases the quality of the image.

REFERENCES

1. Ka Ki Ng and Edward J. Delp, "Background subtraction using a pixel – wise adaptive learning rate for object tracking initialization", IEEE Conf. Video and image processing laboratories (VIPER).
2. Chris Stauffer and W.E.L Grimson, "Adaptive background mixture models for real-time tracking", IEEE Transactions The artificial intelligence laboratory.
3. Mrinali M. Bhajibhakare and Pradeep K Deshmukh, "To detect and track moving objects for surveillance system", IEEE Transactions, vol.no 1, issue 4, June-2013.
4. Vitaly Ablavsky, " Background models for tracking objects in water", IEEE Transactions, vol.no, 2003
5. Sheikh Nasrullah and Dawood Ashrafkhan, "A novel algorithm for real time moving object tracking", IEEE Conf, vol.no, 2011.
6. Jong Sun Kim, Dong Hae Yeom, and Young Hoon Joo , "Fast and Robust Algorithm of Tracking Multiple Moving Objects for Intelligent Video Surveillance Systems" , IEEE Transactions on Consumer Electronics, Vol. 57, No. 3/2011.
7. M. Valera and S. A. Velastine, "A Review of the State-of-art in Distributed Surveillance Systems," IEEE Intelligent Distributed video surveillances, vol.no, 2006.

