BACKGROUND SUBTRACTION FOR EFFECTIVE OBJECT DETECTION USING FCH METHOD

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ABSTRACT - Although many methods of moving object detection have been proposed, moving object extraction is still the core in video surveillance. However, with the complex scene in real world, false detection, missed detection and deficiencies resulting from cavities inside the body still exist. In order to solve the problem of incomplete detection for moving objects, a new moving object detection method combined an improved frame-difference and FCH (Fuzzy Color Histogram) based background subtraction is proposed in this paper. To make the moving object detection more complete and accurate, the image repair and morphological processing techniques which are spatial compensations are applied in the proposed method. Experimental results show that our method can effectively eliminate ghosts and noise and fill the cavities of the moving object. Our proposed work, produces Percentage of color correlation (PCC) 100% compared to previous method.

Keywords - Background modeling, background subtraction, video segmentation, and video surveillance.

INTRODUCTION

Nowadays, there is an urgent need for the robust and reliable traffic surveillance system to improve traffic control and management with the problem of urban congestion spreads. Vehicle detection technique appears to be the weakest link in traffic surveillance and control. Many vehicle state parameters can be detected through surveillance system, including vehicle flow density, the length of queue, average traffic speed and total vehicle in fixed time interval. Vehicle detection technique appears to be the weakest link in traffic surveillance and control [1]. Many traffic state parameters can be detected through traffic surveillance system, including traffic flow density, the length of queue, average traffic speed and total vehicle in fixed time interval. To achieve these goals, in past decades, there have been many approaches proposed for tackling related problems. Among them, the vision-based approach has the advantages of easy maintenance and high flexibility in traffic monitoring and, thus, becomes one of the most popular techniques used in traffic surveillance system [2].

For at least two decades, many researchers have been involved in work that is related to video surveillance to develop more accurate and robust algorithms for moving object detection and segmentation [4]–[8].The segmentation of moving vehicles in outdoor traffic sequences is quite challenging due to various aspects such as unfavorable weather conditions, noisy low-quality videos, and dynamic background. Although there are many proposals that deal with moving vehicle segmentation, there has been limited work to address the aforementioned challenges, which is quite essential for practical deployment of surveillance systems [9].

In this paper, we propose a framework for the segmentation of moving vehicles from video sequence in the following challenging outdoor environments:

- Complex weather conditions, e.g., rain, heavy snow fall, or fog, which cause serious limitation to the visibility of moving objects;
- Repetitive motions such as the swaying leaves in the back-ground;
- Poor-quality and noisy grayscale videos;
- Object of interest with similar color and texture as back-ground;
- Vibration of camera due to wind or the passing of a heavy vehicle.

To provide efficient results, our robust segmentation algorithm not only localizes the object of interest but suppresses the noise that is introduced due to poor-quality low-resolution videos and small camera movements as well. In addition, it reduces the false motion that overshadows the actual objects of interest due to non-conducive weather conditions such as change in illumination and snowy or foggy weather, where the visibility is quite low.

Many researchers have proposed different approaches for segmentation that can broadly be categorized as frame/temporal differencing [10]–[13] and background modeling [14]–[17],[19], [20], [22]–[24]. Frame differencing involves comparing successive frames and categorizing areas that have a pixel difference greater than a certain threshold as foreground regions.

In past decades, numerous research projects aiming to detect moving objects have been carried out in terms of measuring traffic performance during the past decades. There are already several kinds of moving object detection methods, such as, mixture of Gaussian method, edge detection methods and Intensity range based detection method. But those techniques have applicable on static of background videos. This is the main drawback in surveillance systems. In order to avoid those problems, a new technique called frame difference method for dynamic texture scene has been proposed. Background subtraction is conducted by computing the similarity between the observed and the model FCH features (Fuzzy C mean Histogram).

LITERATURE SURVEY

The first known installation of a vehicle detection device occurred at a Baltimore intersection, forming the first semi-actuated signal installation. The detector required drivers on the side street to sound their horn to activate the device, which consisted of a microphone mounted in a small box on a nearby utility pole. Another device introduced at about this same time was a pressure-sensitive pavement detector using two metal plates acting as electrical contacts forced together by the weight of a vehicle passing. This treadle-type detector proved more popular than the horn-activated detector, enjoying widespread use for over 30 years and becoming the primary means of vehicle detection at actuated signals (4).

Detection of moving vehicles is the first step in information extraction from traffic videos. The most widely adopted approach is based on background subtraction. In literature, a median filter method for background modeling can be found in [1, 2]. Toyama et al. [3] developed a three-component system that was the combination of the pixel, region and frame level algorithms to model a background of a video. Wren et al. [4] applied a single Gaussian model to each pixel over a sequence of frames to extract a background image. An adaptive background modeling for real time tracking based on Gaussian mixture model was used in [5-9]. In their work, they represented each pixel in a sequence of frames with a mixture of Gaussians. Stauffer and Grimson (2000) also used motion information along with the color information to model dynamics of background.

Elgammal et al. [10] used non-parametric prediction algorithm instead of Gaussian mixture model to estimate probability density function of each pixel. Even though this technique is better in modeling the behavior of each pixel, several thresholds are needed which make it impractical.

Haritaoglu et al. [11] employed a kernel density estimation method to cope with varying background such as waving trees. They used three values for each pixel: minimum intensity, maximum intensity and maximum intensity difference between consecutive frames observed during training period. A pixel wise median filter over time was then applied to each pixel to distinguish between stationary and moving pixels. It is well-known that background modeling should reflect the real background as accurately as possible, allowing the system to detect the accurate shape of moving vehicles. The detection accuracy can be measured in terms of correctly and incorrectly classified pixels during normal conditions of the vehicle's motion, i.e., the "stationary background" case. Besides, the background modeling should immediately reflect sudden scene changes such as the start or stop of vehicles, so as to allow detection of only the actual moving vehicles with high reactivity, i.e., the "transient background" case. If the background model is neither accurate nor reactive, then the background subtraction causes the detection of false vehicles, often referred to as "ghosts" [7, 11].

In addition, moving vehicle segmentation with background suppression is affected by the problem of shadows [10, 12] which on the other hand makes the appearance and geometrical properties of vehicles getting distorted. Besides, the existence of shadows may cause the close moving vehicles to be segmented as one. In this paper, we propose two simple methods that efficiently provide segmentation and extraction of moving vehicles as well removal of ghosts and shadows detected along with moving vehicles.

Kalyan Kumar Hati et.al [25] Intensity Range Based Background Subtraction for Effective Object Detection, Videos with variant illumination background, textured background, and low motion background are considered for simulation to test the generalized behavior of the scheme. PCC (Percentage of Correct Classification): 95.23%. In the proposed method, PCC is 100%.

PROPOSED METHOD

Conventionally, the first frame or a combination of first few frames is considered as the background model. However, this model is susceptible to illumination variation, dynamic objects in the background, and also to small changes in the background like waving of leaves etc. A number of solutions to such problems are reported; where the background model is frequently updated at higher computational cost and thereby making them unsuitable for real time deployment. Further, these solutions do not distinguish between object and shadow. To alleviate these limitations we propose an intensity range based background model.

Here the RGB frame sequences of a video are converted to gray level frames. Initially, few frames are considered for background modeling and pixels in these frames are classified as stationary or non-stationary by analyzing their deviations from the mean. The background is then modeled taking all the stationary pixels into account. Background model thus developed, defines a range of values for each background pixel location. The steps of the proposed background modeling are presented in *Algorithm 1*

Algorithm 1 Development of Background Model:

1. Consider n initial frames as $\{f_1,f_2, \dots f_n\}$ where $20 \leq n \leq 30$.
2. **for** $k \leftarrow 1$ to $n-(W\text{-}1)$ **do**
3. **for** i ← 1 to height of frame **do**
4. **for** j ← 1 to width of frame **do**
5. $\vec{V} \leftarrow [f_k(i,j), f_{k+1}(i,j), \dots, f_{k+(W-1)}(i,j)]$
6. σ ←Standard deviation of $\vec{V}$.
7. $\boldsymbol{D}(p) \leftarrow \left|V\left(k + (\lfloor W \div 2 \rfloor)\right) - V(p)\right|$, for each value of $p = k+1$, where $l=0,\dots,(W\text{-}1)$ and $\iota \neq \lfloor W \div 2 \rfloor$
8. $\boldsymbol{S}$ ← sum of lowest $\lfloor W \div 2 \rfloor$ values in $\vec{\boldsymbol{D}}$
9. **if** $\boldsymbol{S} \leq \lfloor W \div 2 \rfloor \times \sigma$ then
10. Label $f_{k+(\lfloor W \div 2 \rfloor)}(i,j)$ as stationary
11. **else**
12. Label $f_{k+(\lfloor W \div 2 \rfloor)}(i,j)$ as non-stationary
13. **end if**
14. **end for**
15. **end for**
16. **end for**
17. **for** $i \leftarrow 1$ to height of frame **do**
18. **for** $j \leftarrow 1$ to width of frame **do**
19. $M(i,j) = min[f_s(i,j)]$ and $N(i,j)$=max[fs(i,j)], where s= $\lceil W \div 2 \rceil, \dots, n - (\lfloor W \div 2 \rfloor)$ and $f_s(i,j)$ is stationary
20. **end for**
21. **end for**

Fuzzy Color Histogram (FCH): In this paper, the color histogram is viewed as a color distribution from the probability viewpoint. Given a color space containing *n* color bins, the color histogram of image containing *N* pixels is represented as $H(I) = [h_1,h_2, \dots, h_n]$, where $h_i = Ni/N$ is the probability of a pixel in the image belonging to the *ith* color bin, and N_i is the total number of pixels in the *ith* color bin. According to the total probability theory, h_i can be defined as follows:

$$h_i = \sum_{j=1}^{N} P_{(i|i)P_j} = \frac{1}{N}\sum_{j=1}^{N} P_{(i|j)} \text{ -- (1)}$$

Where P_j is the probability of a pixel selected from image *I* being the *j*th pixel, which is 1/*N*, and $P_{i\,|\,j}$ is the conditional probability of the selected *j*th pixel belonging to the *i*th color bin.

Definition: The fuzzy color histogram (FCH) of image *I* can be expressed as $F(I)=[f_1,f_2, \dots, f_n]$, where

$$f_i = \sum_{j=1}^{N} \mu_{ij} P_j = \frac{1}{N}\sum_{j=1}^{N} \mu_{ij} \text{ -- (2)}$$

P_j has been defined in (1), and μ_{ij} is the membership value of the *j*th pixel in the *i*th color bin

After successfully developing the background model, a local thresholding based background subtraction is used to find the foreground objects. A constant is considered that helps in computing the local lower threshold and the local upper threshold. These local thresholds help in successful detection of objects suppressing shadows if any. The steps of the algorithm are outlined in *Algorithm 2*

Algorithm 2 Background subtraction for a frame *f*

1. **for** i ← 1 to height of frame **do**
2. **for** j← 1 to width of frame **do**
3. **Threshold** $\boldsymbol{T}(i,j) = (1/C)(M(i,j))+N(i,j))$
4. $\mathbf{T}_L(i,j)$=M(i,j)-$\mathbf{T}(i,j)$
5. $\mathbf{T}_U(i,j)=N(i,j)+\mathbf{T}(i,j)$
6. **if** $\mathbf{T}_L(i,j) \leq f(i,j) \leq \mathbf{T}_U(i,j)$ **then**
7. $\mathbf{S}_f(i,j)$ =0 // Background pixel
8. **else**
9. $\mathbf{S}_f$(i,j) = 1 // Foreground pixel
10. **end if**
11. **end for**
12. **end for**

RESULTS

Comparing our results with the previous method is Intensity Range Based Background Subtraction for Effective Object Detection the main variation in previous and our method is Percentage of correct classification (PCC).

In previous, PCC is 95.23%, our results shows the 100% PCC based of FCH (Fuzzy Color Histogram) algorithm.

Fig1: Original Frame

Fig2: Intensity Based Background Detection

Percentage of correct classification (PCC) = 95.23%

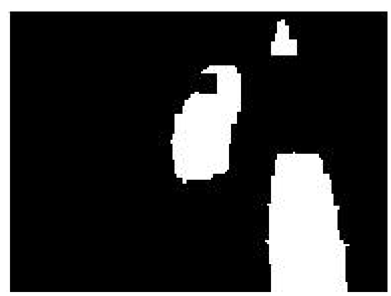

Fig3: Fuzzy Color Histogram

Percentage of correct classification (PCC) = 100%

CONCLUSION

A simple and robust method for background subtraction for dynamic texture scenes has been proposed in this letter. The basic idea is to adopt FCH (Fuzzy Color histogram) in a local manner to minimize color variations generated by background motions. Background subtraction is conducted by computing the similarity between the observed and the model FCH features, renewed by online update procedures. Based on extensive experimental results, we confirm that the proposed algorithm provides the reliable background model in dynamic texture scenes.

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