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VEHICLE DETECTION AND TRACKING TECHNIQUES USED IN MOVING VEHICLES

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ABSTRACT

The difficulty of obtaining the initial background there is the inaccuracy of real-time background update and the difficulty of controlling the update speed in moving vehicle detection of traffic video this paper proposes an accurate and effective moving vehicle detection method which can be used in complex traffic environment. This method first constructs initial background image according to the real-time situation of traffic environment then segmentalizes the current frame into foreground region and background region accurately using the combined method of inter-frame difference and subtraction method. The experimental results show that this method can detect moving vehicles fast and accurately in complex traffic situation. Vehicle detection and tracking applications play an important role for civilian and military applications such as in highway traffic surveillance control management and urban traffic planning. Experimental results show that this method can detect moving vehicles fast and accurately in complex traffic situation.

Keyword- Moving detection; Statistical background model; Intelligence traffic system; Background subtraction.

1. INTRODUCTION

The manpower to manage the traffic is not enough so intelligence traffic system (ITS) appears. Because of the influence like complexity and diversity of road conditions background disturbance and illumination changes of road traditional moving detection methods such as inter-frame difference, background subtractions and optical flow method can't detect the moving vehicles self-adaptively and timely in the complex traffic situation. One of the significant applications of video-based supervision systems is the traffic surveillance. The traffic engineering applications to extract useful and precise traffic information for traffic image analysis and traffic flow. The accuracy of initial background image plays the important role in the performance of vehicle detection. Many other moving object detection methods have been proposed such as W4, statistic background model and dynamic background model algorithm. However, we cannot stop the traffic when we build the initial background image so the w4 method is not suitable for the traffic detection.

2. MOTION VEHICLE DETECTION AND SEGMENTATION APPROACHES

The detection of moving object's regions of change in the same image sequence which captured at different intervals is one of interested fields in computer vision. One of the video surveillance branches is the traffic image analysis which included the moving/motion vehicle detection and segmentation approaches. The research papers have been showed for moving vehicle detection (background subtraction, frame differencing and motion based methods) but still a tough task to detect and segment the vehicles in the dynamic scenes.

1. Background Subtraction Methods.
2. Feature Based Methods.
3. Frame Differencing and Motion Based methods.

2.1. Background Subtraction Methods

The process of extracting moving foreground objects (input image) from stored background image (static image) or generated background frame form image series (video) is called background subtraction, after that, the extracted information (moving objects) is resulted as the threshold of image differencing. So, several researchers work to resolve this drawback by proposed methods on this field. After that, the pixel values updated by the Gaussian probability distribution model these pixel values which are updated from new image in the new image series. Then, each pixel (x,y) in the image is categorized either be a part of the foreground (moving object or called blobs) or background according to adequate amount of knowledge accumulated from the model which mention above using the equation (1) below:

$$I(x, y) - Mean(x, y) < (C \times Std\ (x, y)) \quad (1)$$

Where I(x, y) is pixel intensity, Mean(x, y) is the mean, Std (x, y) is the standard deviation.

An advanced background subtraction technique used to detect and extract features for vehicles in complex road scenes in traffic surveillance. Secondly Principal Component Analysis (PCA) is applied as a low-dimensional statistical method to measure the two histograms of each candidate and support vector machine (SVM) is considered for real vehicle parts classification. This method extracts the size features of vehicles from information that gathered from the distance between ends of front and rear tires for underneath shadow of vehicles to distinguish the existence of vehicles on the lanes.

The information represented as traffic movement images which obtained from a camera assembled on a low position such as the roadside, sidewalk, etc. In addition, a shade removal method is combined with a versatile background deletion approach to take out the mobile vehicles in background images. In addition, they employed a projective floor-level transform to reinforce the expectations of speed persistence and entity volume for forefront form.

2.2. Feature Based Methods

Furthermore the feature based method supports the occlusion handling between the overlapping vehicles and compared with background subtraction method represents a less level from the computational difficulty view. This approach based on learning which employs a set of labeled training data which used for labeling the extracted objects features. A sub region is a technique used to locate the local features which used for recognition nonoccluded and partially occluded vehicles. Principal components analysis (PCA) weight vector used to pattern the low-frequency components and an independent component analysis (ICA) coefficient vector used to pattern the high-frequency components these two vectors were generating by sub regions. Furthermore a multiscale transformation uses the frame elements of image which are indexed by position measure and orientation criterions and have time-frequency localization properties of wavelets also it shows a very high degree of directionality and anisotropy this method called curve let transform.

In this work the Eigen-window approach is used due to it has several advantages such as detect the vehicles even if it changed its path due to veering out of the lanes and also if parts of the vehicles are occluded. This method treats the noise sensitivity and existence of the rough edge on edge detection through developed a new sobel operator which overcomes the traditional sobel shortcomings and the Gabor operator texture edge detection is also used for extracting the features. A low resolution aerial image used as dataset for detection vehicles system this system uses the edges of the car body the edges of the front windshield and the shade as the features for the similarity process.

2.3. Frame Differencing and Motion Based Methods:

The frame differencing is the process of subtracting two subsequent frames in image series to segment the foreground object from the background frame image. The motion segmentation process is the another fundamental step in detecting vehicle in image series and which is done by isolating the moving objects (blobs) through analyzed and assignment sets of pixels to different classes of objects which based on orientations and speed of their movements from the background of the motion scene image sequence. This method accurately used a remote multimodal (audio/video) monitoring system to extract and reconstruct vehicles in real-time motion scenes. The first step a novel background changing method will use for bright changing in video scene and the second step adaptable movement histogram-based vehicles detection is used supported and modernized corresponding with movement histogram in the dynamic view.

A. Statistical Background Model

This method divides Y into several intervals under the YUV color space. To each pixel, we record number of times that brightness value appears in every interval for a period of time, and then find out the interval in which brightness value appears most times, calculate its mean, and then make it as the brightness value of background model at that point. This method has the following two shortcomings. Firstly, for each pixel, if the pixel's actual intensity Y' scatters uniformly in this period, then the number of Y' is relatively small in each interval. So, the obtained Y can't represent the approximation of Y'. Secondly, this method assumes that once the moving vehicles drive into the video, the vehicles will not stop, so this method is not suitable for the traffic environment such as crossroad in which vehicles often have to stay.

B. Background Image Initialization Method Based on Improved Statistical Background Model

Firstly, Calculate expectation value and variance of each pixel, defineμi as gray expectation value of any point *i* in background, σ i 2as variance of

$$\mu_i = \frac{1}{n}\sum_{t-1}^{n}\mu_{it} \quad (2)$$

$$\sigma_i = \frac{1}{n}\sum_{t-1}^{n}(\mu_{it} - \mu_i)2 \quad (3)$$

Where, μ is gray value of point *i* in the *t-th* frame. Secondly, build the initial background image according to each pixel's variance. Variance can represent the pixels' distribution on N frames. This paper selects the class's center whose weight is *w*=max{ *w=1*， *2*， ….， *L* } as the pixel's intensity. If σi> threshold *T*, we can know that the pixel distribute dispersedly in this period, so we obtain the pixel's approximation by averaging in the whole period of time.

I. SELF-ADAPTIVE BACKGROUND UPDATING

In the process of moving vehicles detection, if we want detect the moving vehicles, we must establish a good background updating model. There are several difficulties.

• Disturbance caused by the moving object itself experimental results show that because the color of the vehicles windows is familiar with the road so the real traffic background image is very difficult to be extracted.

• Background disturbance: such as the camera's little jittering, branches' swaying and water wave in the video area. The factor demands a suitable threshold when we get the binary mask by interframe difference method which is the key point of background updating.

• Illumination changes: such as the changes between day and night, natural illumination changes and the shadow of moving object. Taking the above factors into account, this paper proposes a new background update strategy.

A. First Segmentation of the Current Frame:

The current frame image minus the pre-image is to be a difference image. The current background image is *BK(x ,y)*.

$$D_k \text{ (x, y) } = F_k \text{ (x, y) } - F_{k-1} \text{ (x, y)} \quad (4)$$

Where the *Fk (x, y)* is the *k-th* current frame, and the current background image is *BK(x,y)*.

Transform the difference image into the binary

M (I, j) = 0 D(i, j) > T (5)

1 D(i, j) < T

Because the background in the traffic video is changing dynamically, we cannot choose a fixed value as the threshold. This paper will use the difference image to produce a self-adaptive threshold. Most area of the sequence image belongs to the background, so most pixels in the difference images are low value, while only a few pixels are high value.

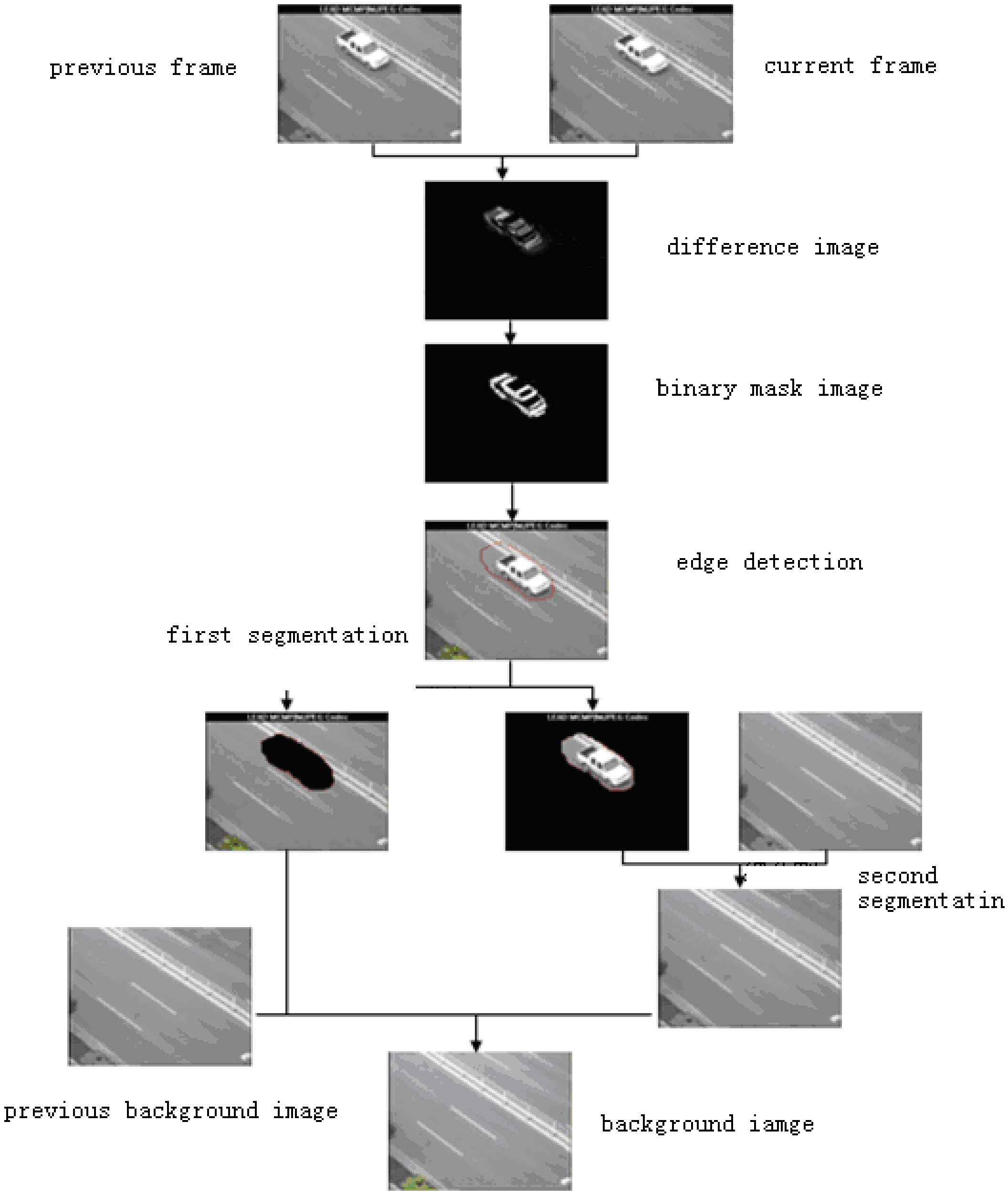

Figure 1. Flowchart of background updating

This histogram of difference image will have high values for low pixel intensities and lower values for the high pixel intensities. We find out the peak of the histogram and use 10% of the peak value as the threshold of the binary mask image. For each pixel in the binary mask, if the value is 0, we can divide it into the background region; otherwise we divide it into the foreground region. But, this segmentation is not accurate enough. Furthermore this will result in many cavities at the last. Because the edge's information of the vehicles produced in the above method will not lost, this paper use the Canny edge detection method which can be used to transform the cavities into connected region to detect the vehicles' edge. At the last of this step, we choose the connected region as the new foreground image.

B. Fine-grained Segmentation of Current Image:

The foreground region will be larger than the actual foreground region and has many cavities. This phenomenon is more serious in the freeway situation because the distance between two frames is further due to vehicles' fast speed. The foreground region in the *k-th* frame after the first segmentation is *FfK(x, y)*, the foreground region in the current background image is *BfK(x ,y)*.

The *FfK(x, y)* minus *BfK(x ,y)* is difference image.

D_{fk} (x, y) = Ff_k (x, y) - Bf_{k-1} (x, y) (6)

According the threshold *T*, we transform the difference image into a binary mask image.

Mf (i, j) = 0 Df (I ,j) > T (7)

1 Df (I , j) < T

We can divide the foreground region obtained from the first step into foreground and background region by equation 6. If the *Mf(i,j)* is 0, we see the pixel (i,j) as background region, otherwise we see it as new foreground region.

3. CAMERA CALIBRATION APPROACEHS

Measuring the vehicle speed and precision of vehicle tracking methods rely on well camera calibration performance and the camera calibration setup may be done in semi-automatically matter or by hand. A new automatic method for segmenting and tracking vehicles applied on a video taken by camera at low angle level relatively to the ground on highway road. There is the expectation of high features which is calculated by joining of region-based grouping procedure, background subtraction, projective transformation and using of plumb line projection (PLP). There is the purpose of this system was classifying the passing vehicles by using these 3D measurements in addition to count the vehicles and assessment their speeds.

4. VEHICLE TRACKING APPROACHES

To track the physical appearance of moving objects such as the vehicles and identify it in dynamic scene it has to locate the position estimate the motion of these blobs and follow these movements between two of consecutive frames in video scene. Several vehicle tracking methods have been illustrated and proposed by several researchers for different issues it consists of:

1. Region-Based Tracking Methods
2. Contour Tracking Methods
3. 3D Model-Based Tracking Methods
4. Feature-Based Tracking Methods

4.1. Region-Based Tracking Methods

The regions of the moving objects (blobs) are tracked and used for tracking the vehicles. A proposed research paper introduced a model-based automobile recognizing tracking and classification which is efficiently working under most conditions. The model provided position and speed knowledge for each vehicle as long as it is visible in addition this model worked on series of traffic scenes recorded by a stable camera for automobiles monocular images. The proposed scheme demonstrated in its work the feature ratio and density to classify vehicles also it used the geometric traits to eliminate the false regions and for more accurate segmentation process is used the shades elimination algorithm.

4.2. Contour Tracking Methods

These methods depend on contours of vehicle in tracking vehicle process .The novel real time traffic supervision approach which employs optical movement and uncalibrated camera parameter knowledge to detect a vehicle pose in the 3D world. It showed well results when it tested for tracking foreground object detection, vehicle recognition and vehicle speed assessment methods.

4.3. 3D Model-Based Tracking Methods

In this paper, the occlusion of vehicles detection process used a 3D solid cuboid form with up to six vertices and this cuboid used to fit any different types and sizes of vehicle images by changing the vertices for a best fit. A unified multi-vehicle tracking and categorization system for various types of vehicles such as motorcycles, cars, light trucks on highway and windy road video sequences has recommended. In this paper a vehicle anisotropic distance measurement achieved through the 3D geometric shape of vehicles. This framework supported advantageous traits such as the flexibility due to it is much free from the scale problem and detects the vehicles from more diagonal visions in addition it is fast when applied to many other applications.

4.4. Feature-Based Tracking Methods

An iterative and distinguishable framework based on edge points and modified SIFT descriptors as features uses in similarity process and these features represents a large region of set of features forms a strong depiction for object classes. The proposed framework showed a good performance for vehicle classification in surveillance videos despite of significant challenges such as limited image size and quality and large intra-class dissimilarities. A linearity feature technique is a proposed line-based shade method which uses lines groups to remove all undesirable shades.

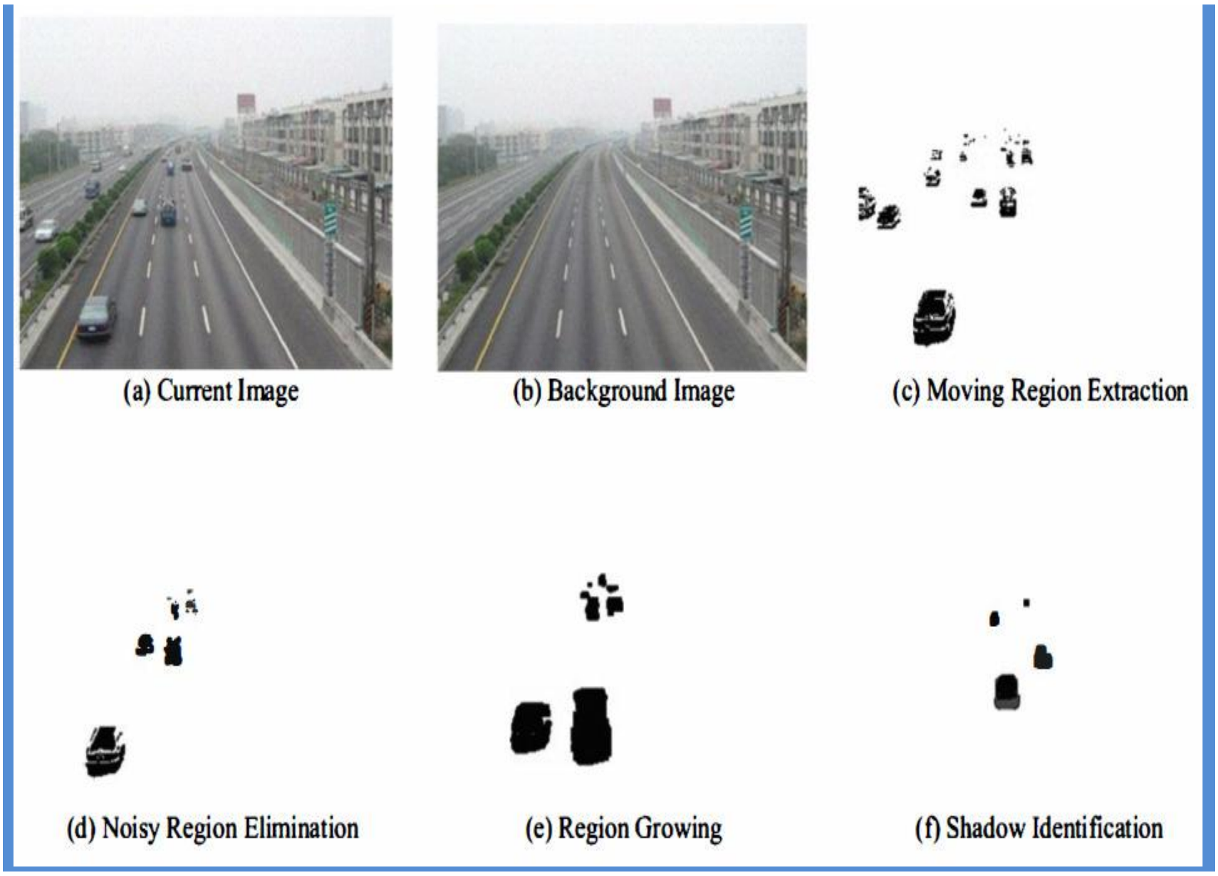

Figure 2: Detection and tracking of moving regions

5. RESULT

Here, we have seen Vehicle detection process on road is used for vehicle tracking, counts, average speed of each individual vehicle & traffic analysis. The system is able to track and classify most vehicles successfully. In a 20 minute sequence of freeway traffic, 90% of the vehicles were correctly detected and tracked. Of these correctly tracked vehicles, 70% of the vehicles were correctly classified. The processing was done at a frame rate of 15 frames/s. Also, when multiple vehicles occlude each other, they are often detected as a single vehicle. However, if the vehicles later move apart, the tracker is robust enough to correctly identify them as separate vehicles. Unfortunately, the two vehicles will continue to persist as a single vehicle if the relative motion between them is small. In such a case, the count of vehicles is incorrect. Another thing to note is that the images we used are grayscale. Since our segmentation approach is intensity based, vehicles whose intensity is similar to the road surface are sometimes missed, or detected as fragments that are too small to be reliably separated from noise. Although our data consisted of traffic moving in only one direction, the tracking algorithm is general enough to work with multiple traffic directions. Also, our data was acquired on an overcast day thus removing the problem of shadows. As described, our system does not handle shadows although preliminary investigations into shadow handling have been positive.

6. CONCLUSIONS

The paper provides a summarizing study on the proposed techniques which are used in traffic video and it focuses mainly in these areas such as vehicle detection, tracking, classification with appearance of shadow and partial occlusion. Also we represent and classify the traffic surveillance systems to three types based on specific methods which are used for developing it and in addition shadow and partial occlusion matters and its available solutions are discussed. These types shows the detailed information that how the traffic surveillance systems uses the image processing methods and analysis the tools for detection, segmentation and tracking the vehicles of the road. We have presented a model-based vehicle tracking and classification system capable of working robustly under most circumstances. The system is general enough to be capable of detecting, tracking and classifying vehicles while requiring only minimal scene-specific knowledge. In addition to the vehicle category, the system provides location and velocity information for each vehicle as long as it is visible.

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