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Recursive Image Segmentation for Vehicular Traffic Analysis

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Abstract: Many methods have been proposed for image segmentation in vehicular traffic analysis using traffic camera video footage. However, isolation of moving objects with perfect object boundaries has been a challenging problem in vehicular traffic analysis. Usually these vehicle objects are extracted inside rectangular boundaries with extra irrelevant background image pixels from other objects included in the analyzed image. Thus using such segmentation methods in vehicle identification using video is not favorable for feature extraction for classification of vehicle category. This work proposes a method to deal with irregular shaped image segmentation for vehicle identification using a recursive algorithm. A binary thresholded image composed of white and black pixels is filtered with a 2D low pass filter to isolate irregular shaped image boundaries of objects. Then recursive image segmentation is applied on the filtered binary image. White pixels in the 2D filtered image are used to identify the presence of the object. If the neighboring pixels of the pixel of interest are also white, then those neighboring pixels are recursively processed the same way to account for the extent of the object. This recursive collection of pixels bounded by an irregular shaped boundary is continued until neighboring pixels are significantly different in color from the pixel of interest. From this recursive image segmentation algorithm, extraction of all pixels of odd shaped objects done in an efficient manner. Accordingly, pixels count, height and the width of the object are recorded. This image segmentation method has been successfully applied to identify vehicle categories in traffic video sequences.

Key Words: Image segmentation, Vehicle identification, Irregular shape

Introduction

Image processing has evolved for better interpretation of images by humans and data storage, analysis and transfer. Current use of image processing has expanded to different fields such as medical, remote sensing, electronics and so on. The applications of image processing like feature extraction, object detection, image scanning have been relied on image segmentation as a pre-processing step. Thus, to find an appropriate segmentation algorithm based on the application and the type of input image is very important.

Several studies exist in the literature on image segmentation, vehicle detection and tracking. For example, Achanta et al**.** (2010) have presented SLIC superpixels image segmentation algorithm based on superpixels which can be used at a pre-processing stage in vision applications. The proposed methodology uses that cluster pixels with a combination of five dimensional color and image plane space to efficiently generate compact and nearly uniform superpixels and adhere well to region boundaries. The efficiency of superpixels has been proved in object category regognition and medical image segmentation. Zivkovic et al. (2004) have presented color histogram based non rigid object tracking. The algorithm is able to robustly track objects in different situations and also can adapt to change in shape and scale. Human faces tracking was the primary goal of this algorithm but as experimentation done, it can be used for other objects also. Ma et al. (2012) conducted a study on Canny edge detection and its improvements. It takes input gray scale image and produces output image showing the positions of tracked intensity discontinuities. The main purpose of this study is to image segmentation and extract shape information thus most of the shape information of an image is enclosed in edges. Rhouma et al.(2013) has presented improving the presence of Hu moments for shape recognition. subdomains, and computing their invariant moments. This division does not result in any extra computations. The result is regular Hu moments tend to give way more weight to pixels that are farthest from the center of gravity used to improve shape recognition. Viola et al.(2001) has presented an approach which describes machine learning for visual object detection which is capable of processing images rapidly and high detection rates. In the domain of face detection the system capable of detection rates comparable to the best previous systems. The methodology can be used to detect vehicle categories in different traffic conditions. Bas et al. (2007) have presented a new traffic video analysis method that accounts for the geometry of the scene where adaptive bounding box size is used to detect and track vehicles according to their estimated distance from the camera. In the proposed methodology vehicle detection is done by background subtraction. To distinguish moving vehicles from the static background, Gaussian Mixture Modeling has been modeled with a background scene. A mask of the road is extracted first to reduce search space. Kalman filter has used for tracking vehicles extracted from background models. According to the results section problems with tracking mostly occurred due to foreground segmentation and cameras are affected from environmental factors. In the past several image segmentation algorithms reported in the literature have used pixel based segmentation, edge based segmentation and region based segmentation (Hoover et al., 1996). These types of models have their pros and cons, and the choice of them in applications depends on different characteristics of images. Even with good illumination, pixel based segmentation methods result in a bias of the size of segmented objects when the objects show deviations of the gray values. Accordingly brighter objects emerge as large ones, while darker objects emerge as small ones. The size variations will not occur if we consider the edges of the image by taking the mean of the object and background gray values as the thresholds. However, the edge based segmentation approach is only possible if all objects show the same gray value or if different thresholds for each object are applied. An edge based segmentation approach can be used to detect image boundaries. This type of highly localized image information is adequate in some situations, but has been found to be very sensitive to image noise. Region based methods are significantly less sensitive such as the effects of noises. However, the region-based methods also have weakness in which they do not make use of local image information and will lead to inaccurate segmentation.

This work demonstrated on, and in part motivated by, the task of vehicle identification. Road traffic congestion has become a major issue in populated cities. Since the goal of our final system is to help the traffic management to predict traffic congestion prioritizing safety and sustainability. To identify vehicular features, Isolation of moving objects with perfect object boundaries has been a challenging problem in vehicular traffic analysis. But how can this be achieved if the segmented moving object contains extra irrelevant background image pixels? However isolation of real life objects with perfect object boundaries have been a challenging problem using above segmentation methods. Usually these vehicle objects are extracted inside rectangular boundaries with extra image segments from other objects included in the analyzed image.

The main objective of this study is to detect the moving objects in a traffic scene and extract them with irregular shaped boundaries for vehicular identification. Although a number of research studies have been conducted in several countries in the area of vehicular identification (Bas et al. 2007, Michalopoulos, 1991). This paper brings a new algorithm for image segmentation for irregular shaped objects consequent to identify vehicle category. The proposed recursive algorithm is most clearly distinguished from previous approaches in its ability to detect irregular shaped images. In other image segmentation algorithms, usually images are extracted in rectangular boundaries with extra irrelevant background image pixels. It is very important to extract only the vehicular image without background image pixels which are irrelevant to moving object for feature extraction and classification of vehicle category. The stability of vehicle classification method is vulnerable to various environmental variations, such as illumination, noise, vehicle shadow, angle of cameras and weather related anomalies in the image.

The remainder of the paper describes our contributions, a detailed description of our experimental methodology and experimental results. Finally concludes this paper and describes directions of future work.

The Proposed Methodology

The proposed algorithm is an image processing algorithm capable of extracting comparatively high percentage of pixels of a moving object. Background subtraction technique in (Radhakrishnan, 2013, Hardas et al., 2015) used to identify moving objects eliminating static objects from a video sequence. A binary thresholded image composed of white and black pixels is filtered with a 2D low pass filter in (Cabello et al., 2015, Gedraite et al., 2011) to isolate irregular shaped image boundaries of objects. Thus the white pixels are considered as the pixels of the moving object. Figure 1 shows a grey-scale frame from a video sequence (left) together with the detected moving objects pixels image (right) is contained white and black pixels. Then the resulting binary image which consists of white and black pixels is analyzed using the proposed recursive algorithm. A set of pixels in which each pixel is connected to all other pixels is considered as a one object. From this recursive algorithm all connected white pixels are recorded to an array. White pixels are used to identify the presence of an object. Subsequently all the objects in an image extract in an efficient manner. Accordingly, the pixels count, height and width of the objects are recorded.

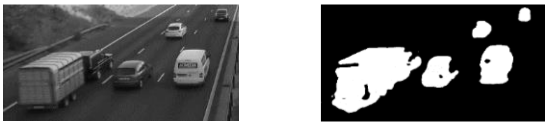

Figure 1: A grey-scale frame from a video sequence (left) together with the detected moving objects pixels image (right)

The Algorithm

These are the steps we have followed for extracting moving objects from a sequence of video frames. A video frame is considered as an image.

Algorithm steps:

1. Convert the color image in to a grey-scale image
2. Use background subtraction to isolate moving objects in the image.

3. Then smooth the image, by taking a 5X5 smoothing kernel over the entire image matrix.
4. Apply a 2D low pass filter to obtain an irregular shaped white blob corresponding to each moving object.
5. Scan the binary image left to right and top to bottom, until you find a WHITE pixel in a selected region of the image.
6. If the pixel is WHITE and not marked in the Scratch_Pad_Image_Array, mark the corresponding grey-scale pixel value to a Scratch_Pad_Image_Array.

   Else check the next pixel.
7. If the white pixel P is within the selected region, four recursive functions call from the

Eastern, Southern, Western and Northern pixels to the P.

Repeat step 5 in each recursive function.

Calculate the sum of pixels in each irregular shaped object.

This recursive collection of pixels bounded by an irregular shaped boundary continues until neighboring pixels are significantly different in color from the pixel of interest.

Calculate the height, width, mid point of the object

If pixel summation > minimum vehicle pixel count, Increase the objects count by 1

Repeat steps 5 and 6

Throughout this entire algorithm maximum percentage of moving objects in a video is captured in an efficient manner. Save the irregular shaped object image to a folder. Image dimension equals to height and width of the object.

Results and Observations

The algorithm was used to extract different odd shaped objects. Moreover, this method has applied to real image frames of videos of vehicles. These videos have been captured from different angles and distinct traffic conditions. The pixels of vehicles have been extracted including the moving casted shadow.

Data identified in each object of a video frame are the number of objects in a frame, pixel count, height, width and midpoint of the object. The required images for the proposed work are acquired with the help of a digital camera. The frame speed of the camera was limited to 25 frames per second. The real time video sequences are acquired with the frame size of 1280 x 720 pixels resolution. In order to check the efficiency of the proposed algorithm, the experiment is performed repeatedly with five number of three minute different traffic videos. In our research six vehicle types have been considered for the results.

Table 1 shows the accuracy percentage of the number of vehicle extraction obtained for different vehicle types. The algorithm was found to have underperformed because of excessive reflection of sunlight and shadow effects leading to erroneous detections and undetected vehicles. The missing number field in table 1 represents the vehicles that were not segmented successfully because they were extracted in combination with other vehicles. The '*' mark denote in the table 1 stands for the average accuracy may not accurate due to insufficient number of data. Average accuracy of the table 1 is 95.6%. Table 2 shows the accuracy percentage of image pixels extraction of different vehicle types. The results depicted in table 2 is evident that the proposed algorithm is well suited for image segmentation. Average accuracy of the table 2 is 93.2%. The average accuracy percentage is an approximate value. The vehicle categories in table 1 and table 2 decided visually and the pixels extraction percentage in table 2 is a visual count.

Table 1: Results of vehicle extraction from the video sequence

	Motor Bike	Car	Van	Three wheeler	Bus	Truck
Actual number of vehicles	91	97	7	44	2	16
Extracted number	83	89	7	40	2	16
Missing number	8	8	0	4	0	0
Average accuracy %	91.2	91.7	*100	90.9	*100	*100

Accuracy - 95.6%

Table 2: Results of pixels extraction percentage of vehicle types

	100% - 95%	95% - 90%	90% - 85%	85% - 80%	Average accuracy %
Number of Motor Bikes	55	27	1	0	94.4%
Number of Cars	45	34	9	1	93.9%
Number of Vans	4	3	0	0	94.7%
Number of Three Wheelers	14	17	9	0	92.8%
Number of Buses	1	1	0	0	92.6%
Number of Trucks	4	9	3	0	91%

Accuracy - 93.2%

Figure 2 shows the irregular shaped vehicular segments obtained as results using the proposed method. The results depicted do not contains irrelevant background image segments from the background due to irregular shaped segmentation of images.

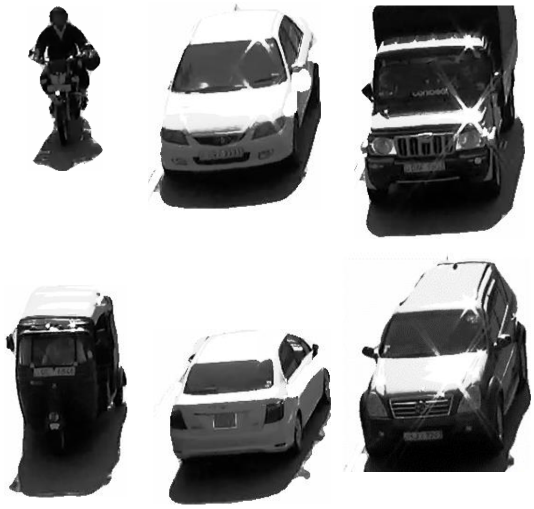

Figure 2: Irregular shaped vehicular segments obtained using recursive image segmentation algorithm

Conclusion

An approach for irregular shaped object extraction with a high accuracy using a new recursive algorithm is presented in this paper. Throughout this paper the work that has been carried out on image processing domain about image segmentation for irregular shaped objects is briefly discussed. This image segmentation method has been successfully applied to identify vehicle categories in traffic video sequences. The proposed method gives a success rate of more than 95% in irregular shaped image segmentation. This paper will encourage the further initiatives to be taken for implementation of work in such a domain. This image segmentation method has been successfully applied to identify vehicle categories in traffic video sequences. The vehicle classification method is sensitive to various environmental variations, such as illumination, noise, vehicle shadow, angle of cameras and weather.

Future Work

As mentioned in the beginning the new recursive image segmentation algorithm will be further extended in order to identify vehicle types in traffic video sequences. The image segmentation is a very vast area with its literature and applications. In future research, this can be extended to identify vehicle categories in traffic video sequences. The feature vectors of each irregular shaped objects extracted using the new image segmentation algorithm could be used to image identification. A state machine for vehicle classifier can be implemented with a machine learning algorithm. However, it is needed to improve robustness against environmental noise, sudden illumination and shadow effects.

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