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Traffic Flow and Average Speed Calculated by Image Segmentation

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Abstract

This paper presents a visual application that allows to calculate the traffic flow and average speed on a section of road by image segmentation . To do this, extracted video images showing the vehicular traffic, where those sections of the image that correspond to movements in the video and match with the movement of vehicles were segmented, then the traffic flow in a section of the road and the average speed of vehicles traveling were measured.

Keywords: Average speed, image segmentation, frames, traffic flow.

1. Introduction

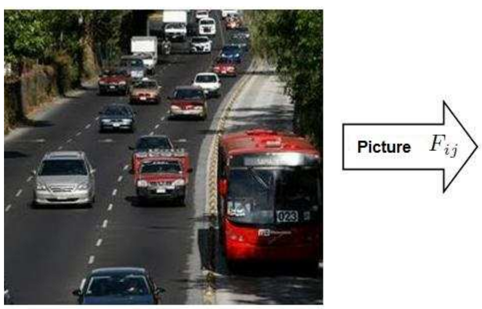
Nowadays the increasing incorporation of vehicles to road infrastructure has caused considerable congestion at various points in big cities and bottlenecks vehicles have become one of the biggest problems that have to deal every day, in addition to the pollution generated [[2], [10]]. To deal with this problem, the main option is to increase the capacity and the efficiency of road networks in terms of existing traffic. Currently the systems of video-surveillance video provided vehicular traffic at almost any time and where a video surveillance camera is installed. So acquiring information by analyzing videos of vehicular traffic can help improve the vehicular flow in road networks [[3], [8]]. If drivers were able to obtain information from vehicular traffic in real time covering the road network, they could choose a route of travel to reach their destination where vehicular flow is less dense, achieving load balance roadways.

The application of image processing and techniques of artificial vision for video footage analysis of the flow of vehicular traffic offers significant improvements over existing methods of data collection[[7]]. For this reason. have been developed several works concerning the flow of vehicular traffic study through image analysis in video sequences, as presented in [[11]] which a system for monitoring traffic and the detection of accidents in road intersections shown, the vehicles are located in real time over the contour of the vehicle, in [[1]] present an algorithm for segmentation and tracking of moving objects in video image sequence applied to monitoring vehicular traffic, in [[5]] present a system that allows analyze the behavior of vehicular traffic on highways and in [[4]] an automated methodology to count moving vehicles on highways through neuro-fuzzy network is presented.

This paper presents a methodology to calculate the vehicular flow and average speed of vehicles on a section of road through video images obtained.

2. Fundamentals

Before getting into detail with the development of this work, it should be mentioned some necessary definitions. Is called frame at each individual digital images captured by a video camera, where a digital image is a two-dimensional function *f(x,y)* of the light intensity (brightness) at a point in space, where *(x, y)* are coordinates of the mentioned point [[6]]. Since it, a digital image is a function *f (x, y)* discretized in both spatial coordinates and in brightness. Often, usually represented as a two dimensional matrix $F_{ij} = (fij)_{mn}$, where m and n represent the size of the image with $f_{ij} = f(x_i, x_j)$ (Figure 1). Each array element is called picture element or pixel.



$$\begin{pmatrix} f(0,0) & f(0,1) & \cdots & f(0,M-1) \\ f(1,0) & f(1,1) & \cdots & f(1,M-1) \\ \vdots & \vdots & \vdots & \vdots \\ f(N-1,0) & f(N-1,1) & \cdots & f(N-1,M-1) \end{pmatrix}$$

Fig. 1: Definition of a digital image.

There are several techniques to detect moving objects in a sequence of continuous frames from video images. Among them is the method of analysis of motion raised by Gonzalo Pajares and Jesús M. de la Cruz [[9]]. This method consists of comparing two different images of an image sequence, this comparison is based on the fact that there are two types of objects within the image sequence: static or background objects and moving objects. Static objects are those that do not move within the sequence of pictures and moving objects are those that can change position during the image sequence. Since static objects are always in the same position, then all images of static objects in an image sequence are identical. However, in an image sequence which contains moving objects changes were present, these changes in the pixels are considered as the contours of the moving object. In a sequence of binary images, motion analysis by image difference is given by:

$$f(v_x) = \begin{cases} 0 & \text{if} \quad Img_x(i,j) \text{ is different to } Img_2(i,j) \\ 1 & \text{if} \quad Img_x(i,j) \text{ is the same to } Img_2(i,j) \end{cases}$$

and in general, for detecting moving objects in a video sequence, first, two consecutive images in the video sequence taken and comparing each pixel between two images is performed, if the pixel value at position *(i, j)* is different between images then corresponds to a pixel motion, otherwise corresponds to a pixel background (Figure 2).

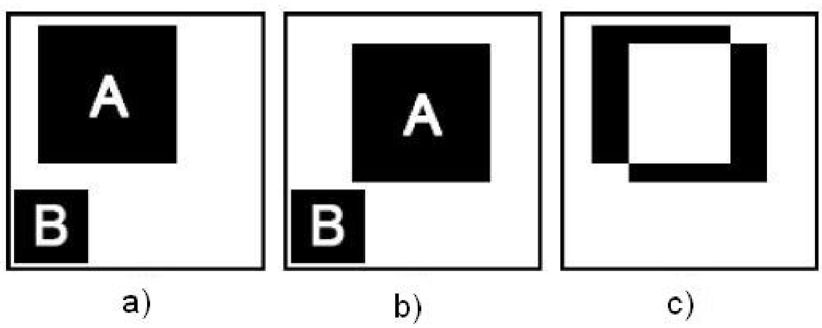


Fig. 2: Analysis of motion image difference. a) Previous picture, b) Current image c) Comparison of images, change areas are marked in black.

3. Proposed Model

First, frames of a sequence of video images were extracted. Each image was applied in average filter to reduce noise with the mask shown in Figure 3.

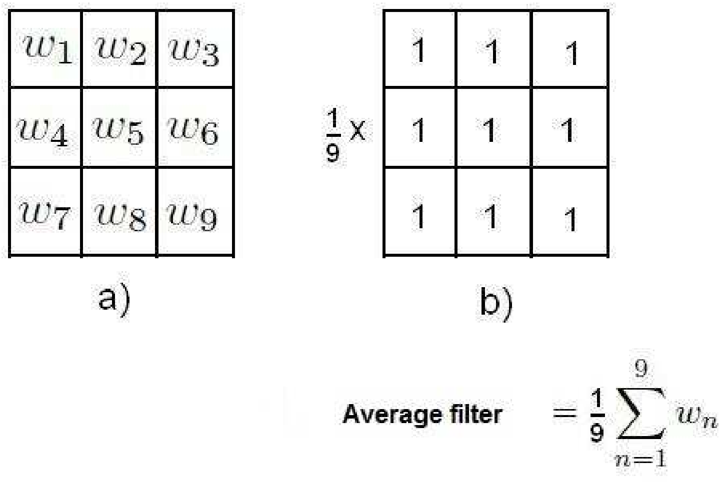


Fig. 3: a) A mask of 3 3 with arbitrary coefficients, and b) Average mask.

Then the technique was applied to detect moving objects proposed by Gonzalo Pajares and Jesus M. de la Cruz [[9]]. Results as shown in Figure 4 were obtained.

Fig. 4: Detection of moving objects, motion detection is shown in green.

As shown in Figure 4, the results of motion detection are not good. The problem of poor detection is due to changes in lighting, which causes the algorithm detects moving objects that were supposed to be static. If we consider the change of illumination is usually not sharp at short intervals of time, then as a solution to poor detection of moving objects, a tolerance value when comparing pixels was considered, thereby, the motion analysis image difference with threshold T is given by:

$$Mov_{ij} = \begin{cases} Img_1(i,j) & \text{if} \quad |Prom(Img_1(i,j)) - Prom(Img_2|(i,j))| < T \\ V & otherwise \end{cases}$$

where *Prom* is the average mask applied to center pixel *(i, j)* and V is the green color used to mark a pixel in motion. The Figure 5 shows the result of applying motion analysis by contrast images with different thresholds.

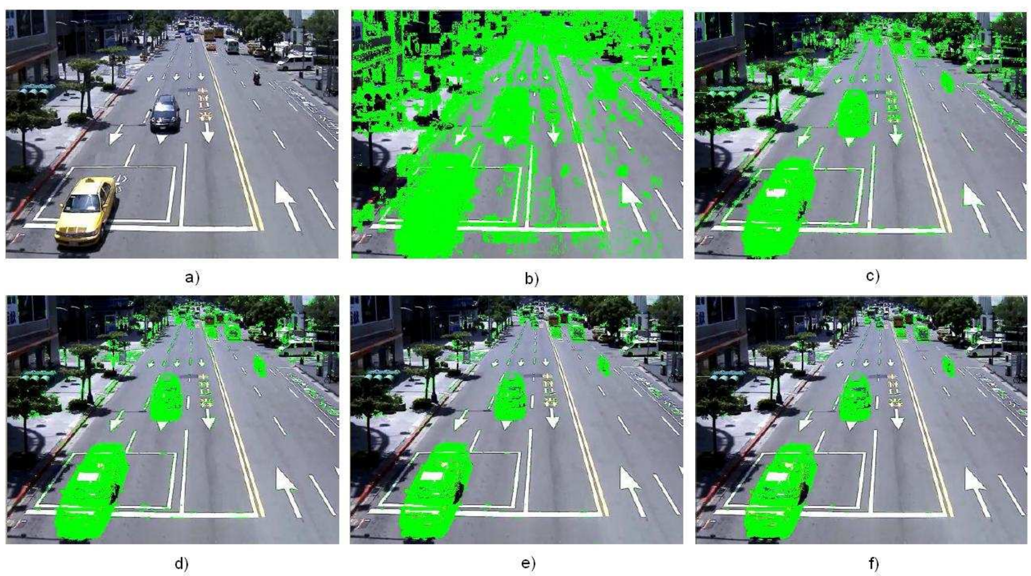


Fig. 5: a) Original image. Results obtained by applying motion analysis by image difference with threshold at b) T = 4, c) T = 8, d) T = 16, e) T = 24 and f) T = 32.

Shown in Figure 5, the best results when applying the motion analysis difference was obtained with a threshold value equal to 32, however, is observed in the image that are still detected as moving objects parts which are not necessary for the purpose of this paper. That is why, immediately the operator of morphological erosion was applied as follows, if a pixel was detected as motion pixel, but in its more neighborhood there is at least one background pixel, then the pixel is considered as background pixel. The Figure 6 shows the result of applying the operator erosion to the image obtained from the motion analysis by image difference with threhold T = 32.

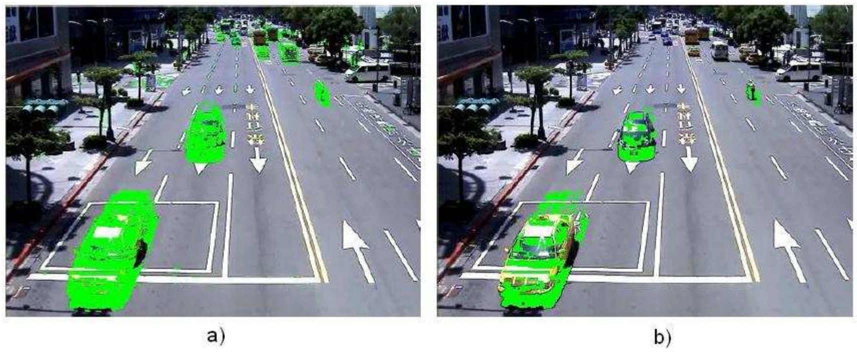


Fig. 6: a) Motion detection by applying motion analysis by image difference with threshold T = 32, b) Result of applying the erosion operator.

To calculate the traffic flow a series of segmented images are taken, in these images is defined a section where the count of vehicles (Figure 7) is made, for it is considered a subsection of the image with the total width of the image and a value of image background is calculated as the next way: The relationship between 1 pixel and 1 meter in the image is calculated, for this, the length in units Avenue subway and the size in pixels of the image is required, both within the section of interest. Thus, the pixels relation between units and units of meters is given by:

$$1m = \frac{Tpx}{T_m}\ pixels$$

$$1mpx = \frac{Tm}{T_{px}}\ methers$$

Where T_{px} is the size of the interested section in pixels and T_m is the avenue´s lenght in meters. Be $V_{max} m/s$ the speed limit on the road section considered. Must be the number of pixels that are advanced by the second (PAS) at this speed is given by:

$$PAS = V_{max} * (\frac{Tpz}{T_m})\ px/m$$

it because each frame obtained from the video takes place in a split second, it follows that the number of pixels advanced per image (PAI) is given by

$$PAI = PAS * T_f$$

where T_f is the time per frame.

Fig. 7: Vehicular flow detection in a subsection of the image.

To calculate the average speed of the next steps was developed:

1. Lanes along the image were defined: This from two points of two images belonging to the same car, the slope of the line that defines the rails using the formula for the slope of a line given for two coordinates of points was obtained. Then the equation

$$C_c = \frac{V_{pz}}{W_c}$$

   where Cc is the number of lanes, V_W is the image width in pixels and W_C is the lane width in pixels, defines the number of lanes in the image.

2. Detection Points: Once located the lanes, are detected and saved the points that representing the vehicles in each lane for each image.

3. Average speed calculate: Once located the vehicles represented by points, the speed is averaged for each channel using the equation $v = d/t(km/h)$. This requires the distance between each pair of points (measured in pixels), calculating the speed in units of pixels/second (px/s) and then turn it to units of km/hour (km/h). To convert units px/s to km/h the following formulas used next:

   $1px = \frac{T_m}{T_{px}} m$
   $V_{pms} = V_{ppxs} X \frac{T_m}{T_{px}} m/s$
   $V_{pkmh} X 3.6 km/h$

where T_{px} is the size of the section of interest in pixels, T_m is the length of the avenue in meters, V_{pms} is the average speed in m/s, V_{ppxs} is the average velocity in px/s and V_{pkmh} is the average velocity in km/h.

4. Results

A computational system developed in programming language C ++ was performed that measures and shows the measurement results of the traffic flow calculate and the average speed in a avenue as shown in Figure 8. The data shown are captured through a video camera, the system shown the location of vehicles in motion marked with red labels and subsection of the road where they performed measurements of traffic flow and average speed is marked in blue. The system has a module presented at the top right that allows indented which is the video camera where is obtained and can save statistics of flow and speed.

Fig. 8: System that detects the average speed and traffic flow.

Conclusions

This paper presents a methodology for calculating the traffic flow and average speed on an avenue through the analysis of extracted images of video security cameras. The proposed methodology allows to locate vehicles moving through the segmentation of images and morphological erosion operation, subsequently calculates the traffic flow and average speed in a subsection on road.

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