TITAN : A traffic measurement system using image processing techniques

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INTRODUCTION

Road traffic management aims at optimizing the occupancy of the space dedicated to vehicles movements. This optimization work implies the knowledge of the traffic flow characteristics all over the network. Pratically traffic engineers perform a spatial and temporal discretisation and then with respect to the type of application, traffic is characterized on each segment and during each time interval, using punctual variables: volume, speed and/or spatial ones: density or concentration (number of vehicles in each segment). Because it is unrealistic to perform measurements all along the road, the flow characteristics are measured on certain segments and rebuilt on others using mathematical models of traffic flow.

Unless important simplifications are made such as in the case of a static model uniquely based on volume conservation, the network modelling implies the use of spatial variables such as density or concentration. (PAPAGEORGIOU 1). Because the existant sensors are not able to provide the direct measurement, the temporal average of the concentration is estimated using the measurement of the time occupancy of the ground detection zone (generally 1 meter square). The direct use of the proportion of the occupancy time (occupancy rate) hypothetizes the uniformity of the vehicle lengths and their speed on each segment. A better estimation of the concentration can be obtained without those hypothesis from both volume measurements and occupancy rates by using filtering techniques (BHOURI et al., 2). Unfortunately in both cases , the concentration is uncertain during congestion, mainly because of the lack of reliability of the occupancy in these conditions.

From the image processing systems applied to traffic, one can expects a direct measurement of the number of vehicles moving on a given road stretch at a given instant. In the case of a big congestion the spatial occupancy (proportion of the axial road length occupied by vehicles) can be measured. Among the known systems, under development after the WADS stop (3), only ABRAMCZUK (4) and TITAN's team are working in that direction. The spatial aspect of the traffic measurement is proving more important in the case of incident detection task. Because existing models are still too inaccurate to enable incident detection with a small number of localised detector stations, the actual techniques use direct measurements (mainly of the occupancy) provided by close stations.

In order to reach as closely as possible a total coverage, measurements should consider zones as wide as possible. Furthermore, there is a necessity to give the operator in charge of the surveillance, some means to confirm or to invalidate an alarm. Hence there are at least two reasons to develop a system able to process images of the widest scenes possible, the ones which can be examined by an operator.

OBJECTIVES

The presented algorithms have been developed using traffic images collected from various scenes covering 100-250 m of a 3 three lanes freeway. Pictures can be front or rear views. The algorithms cope with the possibility of using remote controlled cameras. This means that the system includes features able to re-calibrate the algorithms and to detect the lanes if an operator has moved the camera. Different luminance and traffic conditions are considered below : daylight luminance and average concentration firstly, daylight luminance and saturated traffic secondly, and lastly nocturnal traffic. Because of a previous publication on this subject (5), emphasis is made here upon a new "lane detection" module, analysis of dense traffic and analysis of nocturnal traffic.

In the case of light traffic the following macroscopic measurements can be obtained : concentration, volume, time and space mean speed. All the microscopic ones which can be derived from vehicle trajectories, could also be performed.

In the case of congested traffic only spatial occupancy (proportion of length of road occupied by vehicles) and flow speed can be obtained.

I - DAYLY LUMINANCE AND AVERAGE CONCENTRATION

Three main steps can be defined in the process : in the first one (lanes detection) we try to select almost automatically the region of interest of the scene (lanes of the road). From this image , the relationship between real distances and their measurement on the image, is established. This relationship and the automatic extraction of the lanes enables an almost automatic adaptation of the algorithms to a change in the camera position. Then the vehicles are detected in a second step (vehicle detection). In that step an attempt is made to associate each vehicle one each image with a single marker.In the last step (tracking), trajectories of all the markers are built lane by lane and traffic measurements are derived from them.

Lane detection module

The vehicle detection algorithms make a broad use of geometrical information :

a. the location of the region of interest in the scene ;

b. the connection between distances in pixels (in the image) and distances in meters (in reality).

Everytime the camera is moved (because of a remote control system, a maintenance operation or a wind action), this information must be re-introduced. This could be done manually by an operator ; however, in case of large systems with a big number of cameras, an automatic initialization module would be valuable.

The objective of this module is to detect the traffic lanes, each lane being separated from the others : as a matter of fact, this is sufficient to calculate all the geometric parameters -including the scale factors- provided that the road is located in a horizontal plane and that both the camera height and the lane widths are known. The algorithms are based upon two main ideas :

1. The lanes can be obtained by following the moving vehicles as they pass through the camera scope.

2. Locally, the detections of the lanes may overlap (perspective distorsion) or be partial (no moving vehicle) ; therefore, a reinforcement step is necessary to obtain separate and complete lanes.

These principles led to the following sub-modules :

1) Detection of moving objects :

The time is divided into 8 sec. spaces ; within one space, 64 images are numerized (8 images per second) ; one can evaluate :

their average : $I_{average} = 1/64 \sum I(i)$

their maximum : $I_{maxi} = \max_{i=1..64} |I(i)|$

the maximum of their differences :

$$I_{diff} = \max_{i=2..64} |I(i) - I(i-1)|$$

Afterwards, Min (I_{diff}, $I_{maxi} - I_{average}$)

is calculated, filtered and thresholded ; one obtains a partial detection of the lanes, corresponding to the clear parts of the objects that moved during these eight seconds (picture 1). A similar process can be applied to the dark moving objects, however, when vehicles have lateral shadows, it aggregates the detected lanes.

2) Improvement of the lane detection

The first partial detection is kept as the initial reference image ; 8 sec. later, the second partial detection is obtained and combined with it in order to create an improved reference image.

The process goes on until the reference image is not significantly modified by the new partial detections of the lanes ; at that step, each traffic lane is expected to be almost completely detected and separated from the others (picture 2).

Afterwards, the interesting lanes are selected by keeping only those that cross the bottom, the middle and/or the top of the scope (picture 3).

The analyzed sequences showed good results when perspective distorsion was small and the traffic flow was neither too fluid nor too dense. It should also be pointed out that when the lanes detection module fails, the characteristics of the scene are often not appropriate for a good detection of the vehicles themselves.

vehicle detection

This task is the result of the analysis of one picture at a time (picture 4). This procedure which does not take into account the movements of the vehicles guarantees the possibility of processing the incident images, situations where vehicles are not moving any more. The detection process uses luminance and geometrical features which exist in the picture. Each part of the lanes being broad enough (1,20 m. approximatively) and being a local extremum is considered as a possible marker of a vehicle. Among the dark ones, the front shadow is the most important and the permanent feature. These minima (picture 5) are extracted using geometrically adapted filters. The maxima, which show up clearer than the road (roofs and hoods) are revealed by a morphological transformation (picture 6) and filtered in order to eliminate all too small and too narrow components. These two procedures provide, most of the time more than one marker associated to each vehicle. Hence the third part of the vehicles detection algorithm consists in joining these various markers. By use of simple rules and the distance between the markers, an attempt is made to identify a unique marker for each vehicle(picture 7). At this step the false marker percentage is about 3%.

Vehicle tracking

The above markers are used, lane by lane, to build vehicle trajectories. The position of each vehicle is plotted, time versus road axis in a 2D-map (picture 8). The various points are joined to form the time trajectory of each vehicle.

This time versus position representation of the markers, and the drawing of the trajectories increase the accuracy of vehicle detection (the false detection falls down here close to 0%), by eliminating false markers or, on the other hand by joining markers using a larger interval of time, despite the fact that a marker may have been lost.

Doing so, some particular events (vehicle moving from its traffic lane, standstill vehicle, etc...) may be recognized.

Finally, many traffic variables may be derived from that mapping : volume of traffic, vehicles concentration, (instantaneous or mean) speed of each vehicle, average speed of the traffic in the scene, percentage of the road occupied by the vehicles, and so on.

II - DETECTION IN SATURATED TRAFFIC

During congestion, the interdistances between vehicles are often so reduced that it is impossible to separate them using the techniques represented above. In that case vehicles form queues. The used methodology consists of detecting queues evaluating the length and tracking them across successive images (6).

The process is the following :

a) the dark markers of the vehicles are first extracted and geometrically filtered using the methodology employed in light traffic. Each dark marker is then associated with a specific lane and aggregated with close markers supposed to be belonging to the same vehicle.

b) the white part of the vehicles are also extracted with the already used method.

c) the queues image is built from the upper side of the lanes' image to the bottom side. By dilation, each clear marker is connected with a marker (clear or dark) located below in the same lane. The dilation operation stops when another marker is touched or when the dilation size is greater than a vehicle size (5 meters).

From the queues image (picture 9) the space occupancy can be derived and from the tracking of their front the mean flow speed can be measured.

III - VEHICLE DETECTION BY NIGHT

The images are processed every quarter of a second and each of them is analyzed independently of the others (picture 10). Vehicles are identified by their head lights. The method can be divided into the following steps :

a. First of all the local maxima of the image are calculated, using adapted thresholdings. As a result all headlights are identified, as well as some artefacts (lighting,...) and many reflections on the road and on the vehicles. These false detections will be reduced in the two following steps.

b. Reflections of headlights appear very often as diffuse and less luminous blobs. Thus, a gradient is used for separating the headlights from the reflections. Points that remain at thisstep are asked to be simultaneously local maxima of the image and local maxima of the gradient.

c. The third step consists in merging the headlights and their reflections by an adapted dilation. This transform is based on the fact that the local maxima intensities of reflections are lower than those of headlights and then tend to disappear after dilation.

The image which is retained is the intersection between those obtained in b) and c) (picture 11).

In the next step, headlights of a same vehicle are matched together. This method, which enables us to put a marker on the vehicles, eliminates those which were identified by only one of their headlights (picture 12). Nevertheless they can be detected in the final step of tracking because there is a good probability that they are identified in some following images with their two headlights.

In the final image, the false markers percentage is similar to the one obtained in the daylight process.

CONCLUSION

The processing algorithms have been tested on various traffic situations and luminance conditions and have proved to give good results. Anyway the process will be fully tested when we will have the possibilities to perform all the operations in real time. A dedicated hardware able to process one image in 1/4 second is currently under development. During the different tests, it has been possible to confirm that this new type of sensor is of interest. Not only it enables classical measurements (volume, speed...), but it will offer the possibilities to measure new parameters such as the spatial ones (concentration, lane changes...). Finally it will probably offer the means to develop completely new modelling of traffic behaviour (shock waves propagations, weaving section behaviour) which can complete the modern control techniques of traffic management.

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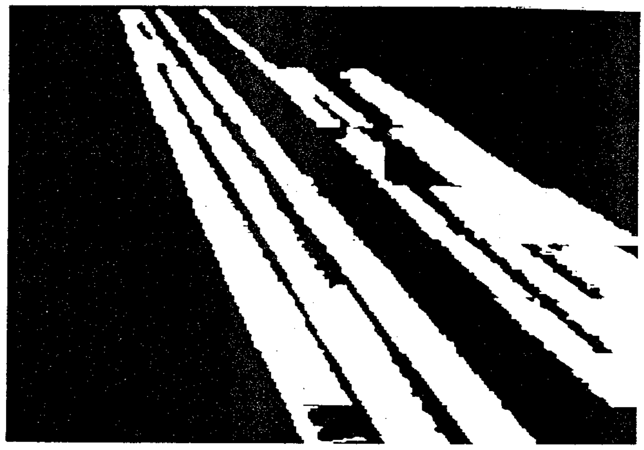
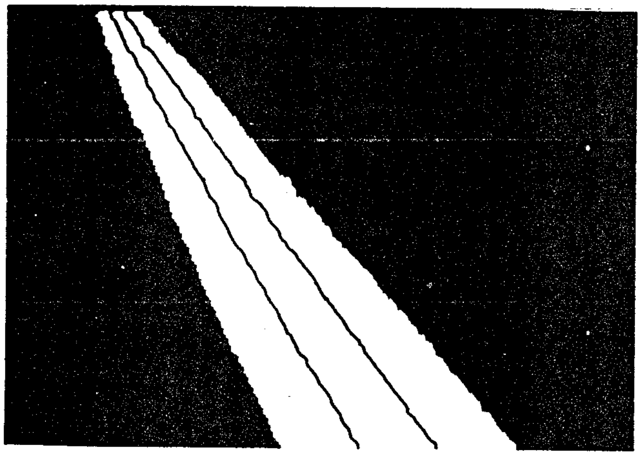
4) ABRAMCZUK T., 1983, tv detector for motorway traffic flow, Swedish Royal Institute of Technology, Stockholm, Sweden, Final report of feasability study.

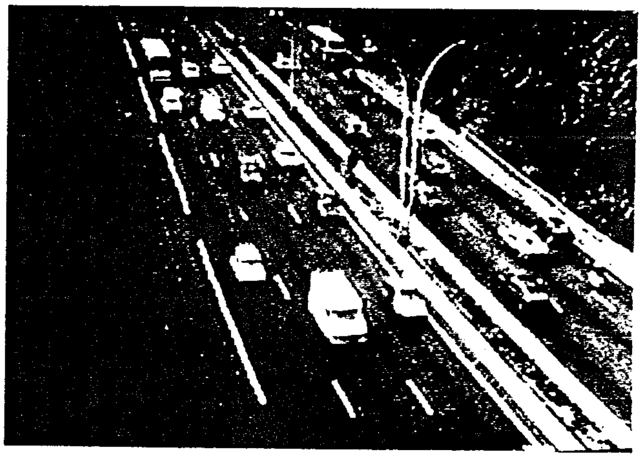
5) BEUCHER S., BLOSSEVILLE JM., LENOIR F., 1987, SPIE Conference, Vol. 848, p. 648-655.

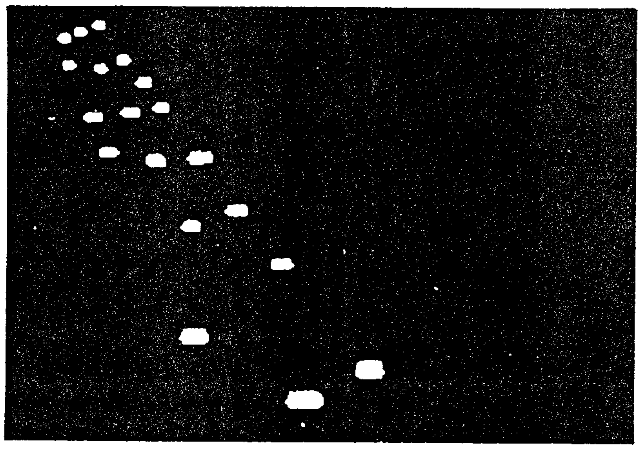
6) VU Hien, 1987, Analyse par caméra video d'un trafic dense, Ecole Nationale Supérieure des Mines de Paris, Option Report.


Picture 1 : Partial detection of the lanes


Picture 2 : Reference image of the lanes

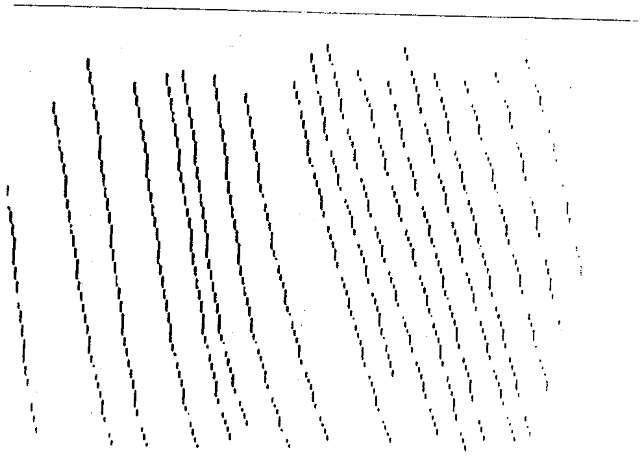

Picture 3 : Final mask of the intersting lane


Picture 4 : Original image before detection


Picture 5 : Dark markers


Picture 6 : Clear markers

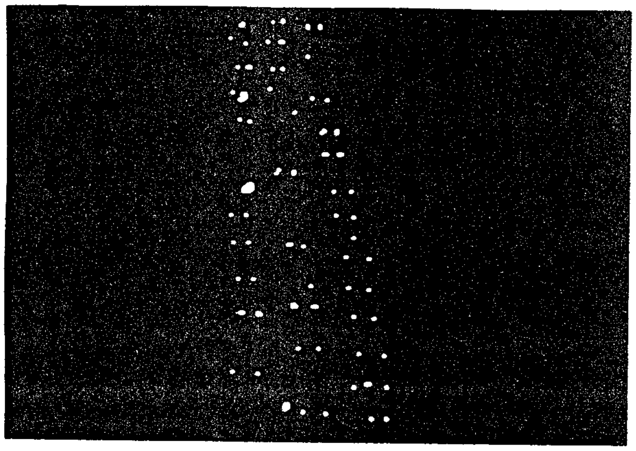
Picture 7 : Final image detection. Each vehicle is marked by a unique marker and its occupancy is evaluated



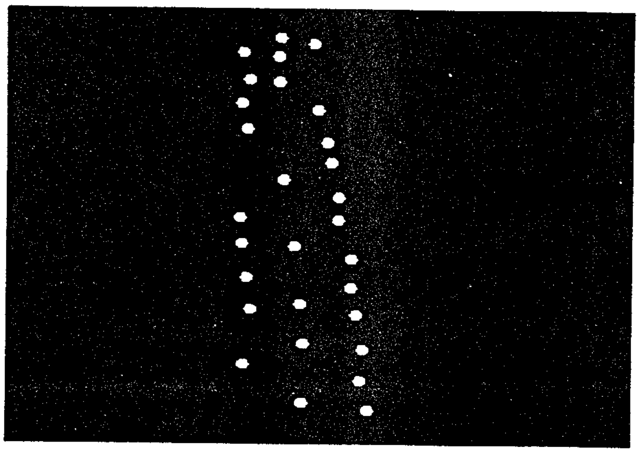
Picture 8 : Trajectories of vehicles across 40 images detection (left lane).

Picture 9 : Detection of queues during congested traffic conditions

Picture 10 : Image of a traffic scene on motorway by night



Picture 11 : Image of the detected points after the 3 steps



Picture 12 : Image of the markers of the vehicles