Intelligent Transportation System Reasoning for Shadow Impaired Traffic Surveillance

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Abstract

Object detection in the field of computer vision stands to be a crucial and critical task for object and scene recognition, employment of object recognition is vast in field of surveillance and artificial intelligence. In this paper, we are presenting an Intelligence Transportation system (ITS) for effective vehicle tracking and traffic analysis. Adaptive motion model along with spatiotemporal particle guiding and template update strategies are available for tracking vehicles using airborne particles from an airplane or UAV (Un manned Aerial Vehicle). We are proposing to apply the same terminology to trace vehicles from front view by locating camera on the lamp posts or signal posts available in congested areas of the city. This method will be utilized for vehicle detection and segmentation by eliminating its shadow duplicate by using IOOPL algorithm. The vehicle details will be recorded in log for future verification.

Keywords: ITS, Traffic Surveillance, Vehicle Tracking, IOOPL, Vehicle detection

I. Introduction

Traffic analysis is a tedious task in cities particularly when there is more congestion in traffic prevails. These traffic congestions occur in areas where the demands in traffic cannot be met or serviced. The application of sensors does not seem to be far effective for vehicle tracking in such areas. This is where automated vehicle tracking using airborne image sequences can be employed. The efficient tracking methodology is used to track individual particle cloud in the search area based on the airborne particles in the vehicle boundary such as humidity, dust etc. There are conventional methods along with spatiotemporal particle guiding and template update strategy approaches are used to filter the particles representing the vehicle in order track the vehicle. However the available method does not store the information of the tracked vehicles in the log can be used for future reference. We propose the usage of particle filtering concept to capture the vehicles from front using cameras installed on lamp posts available in congested areas.

ITS refer to the integration of information and communication. Information refers to the stand alone data that the user would get from video surveillance cameras and traffic analysis results. Communication refers to the C-ITS (Cooperative Intelligence Transportation System) information from the transportation infrastructure. C-ITS refers to the pervasive capability of vehicles in terms of taking actions instantaneously with respect to the unstable environment. This includes various in-car technologies such as ABS (automatic breaking system) and other such pervasive capabilities in order to enhance road safety and driver experience.

Intelligence transport system is generally used to improve Particle filters are normally employed for the purpose of filtering out the particles individually from a congested environment where it is difficult to locate the number of particles individually. We employ these particle filters for the purpose of tracking each and every vehicle travelling on the road individually. These filters help us to track down the individual vehicle trajectories effectively which is based on the calculated state vector *x* for each vehicle. The vehicles are represented with the help of rectangular region of fixed size. The state vector value is calculated by the particle filter by employing the concept of Sequential Importance Resampling method [5]. The main idea is representing the posterior $p(xt|y1{:}t)$, at time t and the sequence of measurements are given as $y1{:}t = (y1, . . . , yt)$. New particles are sampled from the importance function at each step. The importance function is to be chosen as prior, which in turn indicates the motion model of each vehicle. After which, the associated weights are calculated using the principle of sequential importance sampling and the results are normalized with respect to $\sum_{i=1}^{N} \mathrm{w}^{\mathrm{i}} = 1$. The calculation of weights involves evaluating the likelihood function which is determined with the help of observation model. A resampling procedure is done to avoid degeneracy of particles. The resampled particle set is generated by simulating new samples with respect to the old particles weight distribution. The set of weighted particles are thus replaced with the set of uniformly weighted particles. The performance of these particle filters are determined by the choice of importance function. The approximation of the posterior would give us irrelevant results if the importance function is not chosen well. However, particles cannot be directly sampled from this likelihood function as it requires other strategies to integrate the current measurements into sampling process. Finally, weighted mean shift clustering of particles is done. It is important to note that each vehicle is tracked with the help of an individual tracker. If we use a joint state particle filter for tracking multiple vehicles that would ultimately increase the computational complexity to a greater extent.

We the road safety, transportation, economic performance and environment existence. ITS can be applied to any short of transportation such as road, air, water, rail and the service applicable for both passengers and freight transport.

II. Related Work

Objects are usually embedded into context. Object detection task can be done with the help of Visual context, but it doesn't work in object tracking Helmut Grabner1 et al. The author proposed studies that used to determine the object of interest position, his approach exploits the General Hough Transform Strategy. By using this approach the object position can be evaluated without viewing it directly (e.g., fully occluded or outside of the image region)[1].

An IOOPL method is obtained for shadow detection and removal. The original image is segmented first to remove false shadows. Inner-outer outline profile line matching is used for shadow removal, respect to the shadows boundary line to get original image. The authors have used a shadow removal method based on IOOPL for the purpose of recovering the shadow areas in an image. The shadow boundary separating the shadow and non-shadow regions represents the same type of object with respect to the probability data. The authors have also concluded that the shadow boundary can be contracted inward and expanded outward for the purpose of identifying the inner and outer outlines of the object. This information can be used for generating the outline profile lines. This method is proposed by Hongya Zhang [2].

Jens Leitloff et al have worked on vehicle tracking in high resolution satellite. Since most of the vehicle tracking scenario are based on fixed installed sensors available on bridges and also with the help of cameras, the major part of the traffic available on main roads could not be observed properly. Due to the fact that satellites can provide large scale image even with higher resolution with the help of optical sensor system, the authors have proposed a methodology for detecting vehicles effectively from optical satellite images. The methodology contains a combination of Adaptive Boosting and Haar like features for generating hypothesis for each vehicle. A technique was also used in their proposal for the purpose of detecting vehicle queues and to avoid merging of vehicles in different illumination changes .The authors have also described an approach for detection of vehicles that are either moving or stationary using which the speed of the vehicles also can be determined [3]. Xianbin Cao et al have worked on Airborne Vehicle detection to be equipped in UAV (unmanned aerial vehicle). Though these systems are having certain merits, they have several disadvantages in terms of scene complexity, UAV motion. In order to overcome these demerits, the authors have proposed a new framework of multi motion analysis for the purpose of detecting and tracking vehicles from UAV [4].

III. Vehicle Tracking Using Airborne Particles

A. *Efficient Motion Model*

There are conventional methods for tracking vehicles efficiency in many ways since it tracks a vehicle even when the motion model doesn't fit the original motion of the vehicle which includes auxiliary filters [7] and deterministic search [8] Isabella Szottka et al [5] have worked effectively on Advanced Particle Filtering for Airborne Vehicle Tracking in Urban Areas. The authors have designed the importance function based on the motion model of the vehicle which includes current measurements that helped them in placing the particles in region of high likelihood. There is another important property to be considered regarding the airborne particles which is white noise. The spreading of particles across the search space is determined by the variance of the noise. If the variance of noise is higher, it enables the particles to capture the abrupt motion of the vehicle which in turn increases the efficiency of the tracker. A small noise may concentrate the particles at the position which is predicted by the motion model. This represents the preciseness of the tracker. They have made sure that the efficiency and preciseness should be balanced at any case.

The particles were normally sampled in a consecutive manner and their weights were determined. The authors have assumed that the weight ranges between 0 and 1. The noise increases monotonically staring from 0 and reaches a maximum value σ_{max} , which is usually determined by the limits of the safe driving condition of the vehicle. The range of increase in noise depends on the weight of the previously sampled particle, the standard deviation of the noise and the index i of the current particle. The increase in noise would be moderate as long as the particles obtain a high weight. This specifies that the vehicle is tracked correctly which reduces the chance of false alarm. The noise increases strongly if the particle weights are low in order to spread out the particles in a wide area to capture the position of the vehicle. This property of the efficient model enables the noise to adapt to the quality of the sampled particles which leads to a more efficient search space.

The particles are preceded in descending order with respect to their weights before resampling in the previous step. Particles with high weights represent the exact vehicle state and the notion model without noise represents the true motion of the vehicle and it propagates to capture the vehicle in the next frame.

B. *Spatiotemporal Guiding*

The information of the closely located vehicle (near the target vehicle) can be used to provide knowledge to the tracker regarding the path to be taken by the target vehicle. They have utilized a method to understand the road map layout from the driving directions of the vehicle which are closer to the targeted vehicle.

The authors said that a vehicle would most probably move in the direction of the vehicle moving before it in a highway. In order to integrate this into the tracker, the authors are changed the direction of a fraction of particles which obviously moves in the direction of the vehicle moving in front of the target vehicle. Replacing the direction of the fraction of particles is determined by the quality of the last estimate of the state of current vehicle along with the estimate of the current vehicle. The greater the fraction, last estimate from the current vehicle is less reliable and more reliable the estimate from the closest vehicle. The quality of the estimate is determined by the weight of the corresponding cluster from the mean shifting algorithm. The fraction of particles F from the total number of N particles that is assigned the new direction id determined by

$$F = 4w_c(N- w_{t-1})$$

Where w_c represents the weight of the state estimate of the closest vehicle and w_{t-1} represents the current vehicle weight estimate in the last frame. The factor 4, which is meant for scaling, is determined experimentally. This process may misguide the particles at junctions or turnings where the succeeding may take another way instead of taking the way in which the target vehicle moves. However remember that only a small fraction of particles F is taking the direction of the successor and it is impossible to reach the total number of particles N which in turn increases the tracker efficiency.

C. *Template update Strategy*

The tracker would be having a template for each tracking vehicle which would be compared with the newly recorded image every time. But due to the low frame rate along with the illumination changes, the blurred image updated into the template would cause template drift problem to occur. To overcome this, the authors have make the tracker update template based on both shape and color histogram since if any one of these two alone is considered, there is a great chance of updating the template in a wrong way [5].

IV. Airborne Vehicle Tracking From Front Camera Images

Though the work of Isabella in [5] has lot of advantages in vehicle tracking, it has several constraints which are to be noted such as:

[a] The camera used for tracking vehicles is always in motion along with the traffic.

[b] In addition to that, the view used in their research was top view.

What would be the case if these constraints are not met? We have conducted our research in a way of answering the above question in order to enhance this efficient existing methodology. To provide an answer to this query, we have considered the traffic videos recorded using static cameras attached to the signals or lamp posts which are available in congested area of the cities. This approach does not satisfy the given constraints since the camera is static and the traffic is recorded from a camera placed at the front not at the top.

Particle filters are used for robust tracking of vehicles .These filters are normally employed for the purpose of filtering out the particles individually from a congested environment where it is difficult to locate the number of particles individually. We employ these particle filters for the purpose of tracking each and every vehicle travelling on the road individually. These filters help us to track down the individual vehicle trajectories effectively which is based on the calculated state vector *x* for each vehicle. The vehicles are represented with the help of rectangular region of fixed size. The state vector value is calculated by the particle filter by employing the concept of Sequential Importance Resampling method [5].

The main idea is representing the posterior $p(xt|y1{:}t)$, at time t and the sequence of measurements are given as $y1{:}t = (y1, \ldots, yt)$. New particles are sampled from the importance function at each step. The importance function is to be chosen as prior, which in turn indicates the motion model of each vehicle. After which, the associated weights are calculated using the principle of sequential importance sampling and the results are normalized with respect to $\sum_{i=1}^{N} \mathrm{w}^{\mathrm{i}} = 1$. The calculation of weights involves evaluating the likelihood function which is determined with the help of observation model. A resampling procedure is done to avoid degeneracy of particles. The resampled particle set is generated by simulating new samples with respect to the old particles weight distribution. The set of weighted particles are thus replaced with the set of uniformly weighted particles. The performance of these particle filters are determined by the choice of importance function. The approximation of the posterior would give us irrelevant results if the importance function is not chosen well. However, particles cannot be directly sampled from this likelihood function as it requires other strategies to integrate the current measurements into sampling process. Finally, weighted mean shift clustering of particles is done. It is important to note that each vehicle is tracked with the help of an individual tracker. If we use a joint state particle filter for tracking multiple vehicles, that would ultimately increase the computational complexity to a greater extent. In order for efficient tracking of multiple vehicles, we propose the use of IOOPL algorithm. The block diagram for the proposed approach is shown in figure 1.

Traffic surveillance is done with the help of front camera and the noise is removed from the recorded video and the frames are encoded. The next step is the elimination of background which is followed by the detection of edges. The next step is the removal of shadow [9] and the individual cars in order to identify cars separately from a congested traffic videos.

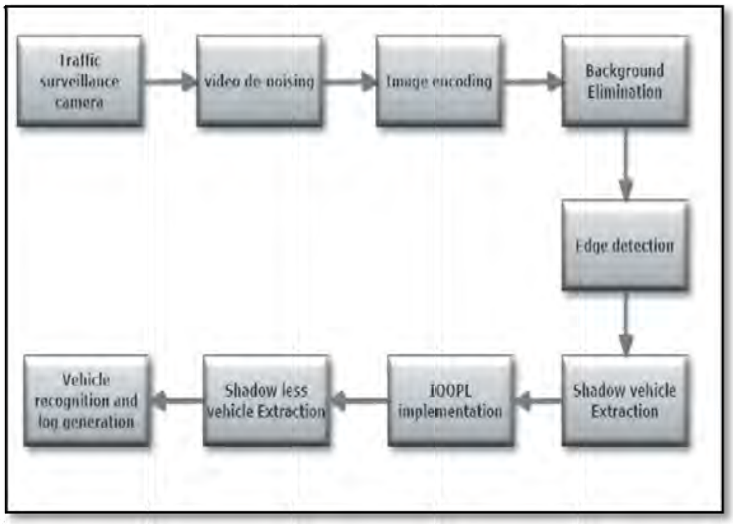

Fig.1. Block Diagram for Traffic Surveillance using IOOPL algorithm

The resultant frame from the previous step is followed by the treatment of IOOPL algorithm. The main use of this algorithm is the efficient removal of shadows from the target vehicles in order to identify them along with the boundaries and edges detected clearly. Shadow removal [10] employs a series of steps. We extract the inner and outer outlines of the shadow boundary. The indication of inner and outer outline lines are done by the inner–outer outline profile lines (IOOPLs). The grayscale values of the corresponding points on Homogeneous sections are obtained through IOOPL sectional matching. At the final stage, we use the homogeneous sections, the relative radiation calibration parameters between the shadow and non-shadow regions in order to separate them and shadow removal is performed. In addition to this, we have employed the use of spatiotemporal bottleneck mining (STBM) [6] which is explained in the following section.

A. Back end system

OBU would be having three states namely dispatched, occupied and available based on the state of the vehicle (here we are considering a taxi). There would be a dispatching center, which decides each time which taxi is to be dispatched next. It would be having all information about all vehicles with respect to the data received from OBU. The normal function of OBU is to record the speed, traffic and position of the vehicle with respect to the predefined rules in OBU. All the traffic information across the way since the taxi starts from its source until it reaches its destination would be recorded and will be given to the back end system via the mobile network. Each packet uploaded into the backend system would be considered as a TIS (Traffic Information Spot) which is reported to the backend system every 15 minutes when the taxi gets dispatched. There is another term called TNS (Traffic Network Snapshot) which usually provides a global view of traffic status. Traffic status on a weekday would have 8 snapshots. It is to be noted that all these data such as TNS, TIS would be stored in TIDB (Traffic Information Database).

STBM does the following:

(a) The first step is to collect, clean and transfer data from LBS into TIDB by identifying the vehicle id along with its location and also integrating urban road network database in GIS (Global Information System).
(b) The above generated traffic information would be stored in TIDB containing TIS and TNS.

(c) Next we can categorize STPs by object and area level patterns which are mined from TIDB using any kind of data mining process.
(d) Object level patterns identify the features of congested network objects which are then transformed into STB. Area level patterns are used to identify traffic demands which are then transformed into STB using SHC (Spatiotemporal Heuristics Algorithm).

The implementation of IOOPL algorithm is done in several steps which involve individual removal of boundaries in the left, right, top and bottom corner of the frame. The piece of code used for the extracting frames is shown in figure 2.

```
aviobj=aviinfo('traffic .avi');              %To Read the video information
 tnf=aviobj .NumFrames;                      % To extract the number of frames in the video
for i=1:tnf                                  % Loop for all videos frames
img=aviread('traffic .avi",i) ;              %Read the i th frame from video
figure(1),imshow(img .cdata);                %Display it as a car
[fname,err]=sprintf('Frame %d .jpg',i);      %Create a text file with frame number
imwrite(img. cdata,fname);                   % Write the frame into jpg file
end
```

Fig.2. Piece of code for frame extraction

V. Experimental Results

The experimental result have been conducted with a frame form the default traffic video available from the MATLAB video dataset and the identification of individual cars after removing the background and detection of edges which is shown in figure 3. Experimental results have proved that an acceptable level of accuracy have been achieved with the help of IOOPL algorithm. Even though region growing algorithm can achieve effective results when we track vehicles from the top and is also notable that the vehicles and the camera should be in motion. But when we use it while tracking from the front, this will not work out and that's why we make use of IOOPL algorithm in our proposed methodology.

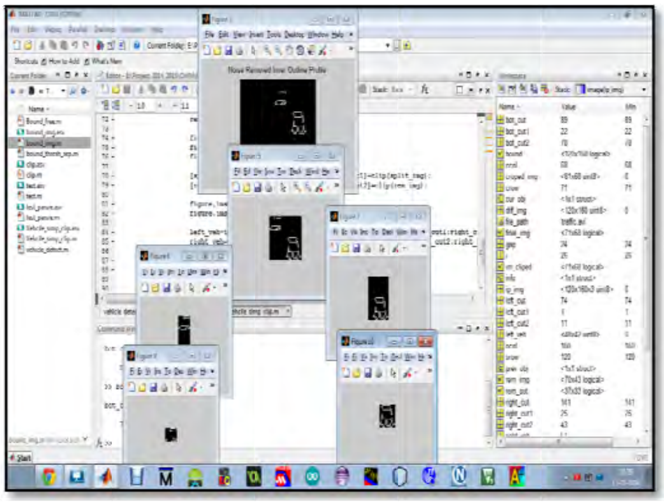

Fig.3. Identification of individual cars

VI. Conclusion

A successful framework for employing video processing algorithms in the traffic surveillance is analyzed and implemented using MATLAB tool. The proposed framework has the advantage of parallel processing multiple vehicles in a single video frame with high precision IOOPL algorithm. The estimated time consumption of the proposed algorithm will vary based on the hardware processor performance and a PENTIUM I5 processor is the least requirement for the high speed vehicle tracking the implemented vehicle detection and extraction in a traffic video will be extended for vehicle recognition in the fore coming phase of work with the text transcription of the classified vehicle status.

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