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Road Surveillance using Gaussian Mixture Model for Birth and Clutter Events in Object Tracking

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Abstract - In video Surveillance for real time images, particularly, when applied for vehicle tracking in roads, complexity arises due to the fact that multiple objects or vehicles appera or disappear from the scene. The modeling of a road is a multi- target environment, where multiple targets are present in the scene. The appearance and disappearance of the targets are modelled by Gaussian Mixture Model (GMM). The model developed was used by Probability Hypothesis Density (PHD) filter. The PHD filter utilizes the contextual information so that occluded targets can be identified. The tracks for entered object, hidden and then appearing object can be extracted from the video images.

Keywords - *vehicle tracking, video surveillance, Gaussian mixture model, PHD filter.*

I. INTRODUCTION

Vehicle Tracking by Image processing techniques is a herculian task due to the limitations in performance introduced by object detectors that generate noisy observations under illumination changes, and occlusions [1]. Vehicle Tracking is a sub-problem under multi-target tracking. Any algorithm developed for vehicle tracking can also be extended for ballistic missile defence (reentry vehicles), air defense (enemy aircraft), air traffic control (civil air traffic), ocean surveillance and battle field surveillance. The actual difficulty involved in the vehicle tracking is with the association of tracks with respective targets, occluded target identification, unknown targets (targets entering the scene) [2, 3]. Even though the performance of the vehicle tracker depends on the scene and characteristics of capturing device, use of contextual information plays a vital role in improving the spatio- temporal performance [4].

Bayesian Filter is popularly used for filtering noisy observations in target tracking. Bayes filter uses a dynamical model to predict the target state and then updates the resultant distribution using the new observation [5,6]. Multi-target Baye's trackers account for target birth and death, clutter and missing observations, and smoothening the input both in space and time. Association of data with targets is an intrinsic problem associated with multi-target tracking. Multiple Hypothesis Tracking (MHT) and its variational techniques addresses the issues of propogation of hypotheses in time [7]. The observations are weighed by their association probabilities in Joint Probabilistic Data Association Filter (JPDAF), and multi-target Filter [8]. Symmetric Measurement Equations and Random Finite Sets (RFS) differ from the traditional tracking algorithms by avoiding explicit associations between targets and measurements [9]. In the Random Finite sets method, collection of each target is termed as 'set valued state' and collection of each observation is termed as 'set valued observation'. RFS suffers from the problem of allowing dynamically estimating multiple targets in the presence of clutter and association uncertainity in Bayesian filtering framework [10].

In this paper, an algorithm for vehicle tracking is established. First, automatic, and interactive feedback is employed to extract scene contextual information. Bayesian modeling based on Probabilistic Hypotheses Density (PHD) filter is employed to register the appearance of new targets. Reappearing targets and disappearance of the same are also modeled using bayesian target tracker. In this context, Gaussian Mixture Model is used to model the birth (appearance) and death (disappearance) of targets. Then the models can be used to modulate the filter response corresponding to the location of targets. Background subtraction is employed in this method to help in identifying targets over an existing scene. The results are evaluated using outdoor surveillance dataset.

II. MULTIPLE VEHICLE TRACKING

The algorithm for multiple vehicle tracking accepts the video images of the road. The video images captured are converted to still images at the rate of 30 pictures per second. From the still images, object segmentation is to be applied to identify the vehicles within the track. Figure 1 shows the flow chart for tracking multiple vehicles from video images taken.

III. SEGMENTATION AND VEHICLE IDENTIFICATION

Background subtraction is employed to separate the moving objects from the background. Image of the background is obtained usually with no moving objects. This can be automatically obtained by an algorithm which checks for movement using continuous subtraction of current still image from previous images. If there is no movement for about 10 minutes then, such image is considered for reference in background subtraction. Sometimes, the image of the road taken at a time when no traffic is present can be selected manually to give as reference. But the automated back ground subtractor helps to ensure there is no manual interaction required and the whole algorithm can be implemented in an automated way.

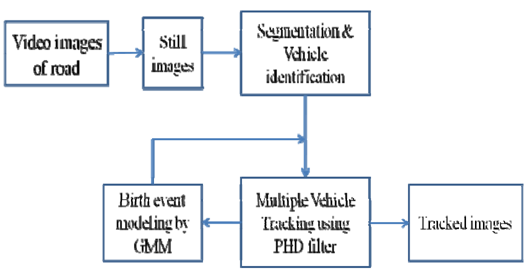

Fig.1: Flow chart for Multiple Vehicle Tracker

Background subtraction automatically leads to segmentation of objets unless there are object clutters. For vehicle identification, templates of vehicles are kept in the database and bayesian neural network is employed to identify vehicle and update the database when new vehicle is presented to it. For vehicle identification, templates of vehicles, human beings, pet animals like dog, cat are included so that the network is able to give proper identification of the vehicle with less misidentification errors.

IV. MULTIPLE VEHICLE TRACKING USING PHD FILTER

Once vehicle is identified, the target, here, the vehicle, is enclosed by a rectangle and is called the target area. The target area be represented by a rectangle of $l \times b$, centered at $\left(y^{(1)}, y^{(2)}\right)$. The single target state is represented by the set of centre points of the target, speed of the target and its size. It is given by $x_k = \left(y^{(1)}, y^{(2)}, sy^{(1)}, sy^{(2)}, l, b\right)$. For Multiple target definition, multi target state is defined by X_k and its corresponding measurements of speed and size is represented by Z_k. To track the vehicles, it is important to model their movements [11]. To estimate the movement of the vehicles, prediction of the objects being in state X_k, given all the observations in $Z_{i:k}$ upto time *k*, followed by updating is executed.

The Prediction step involves computing *prior pdf,*

$$p_{k|k-1}(X_k, Z_{1:k-1}) = \int f_{k|k-1}(X_k, X_{k-1})\, p_{k-1,k-1}(X_{k-1}, Z_{1:k-1})\, \mu(dX_{k-1}) \tag{1}$$

where $p_{k-1,k-1}\left(X_{k-1}, Z_{1:k-1}\right)$ is obtained from the previous iteration,

$\int f_{k|k-1}\left(X_k, X_{k-1}\right)$ is the transition density

μ is an appropriate dominating measure,here taken as 1.

The update step uses the Bayes' rule once the observation at time *k*, Z_k is available.

$$p_{k,k}\left(X_k \mid Z_{1:k}\right) = \frac{g_k\left(Z_k \mid X_k\right) p_{k,k-1}\left(X_k \mid Z_{1:k-1}\right)}{\int g_k\left(Z_k \mid X_k\right) p_{k,k-1}\left(X_k \mid Z_{1:k-1}\right) \mu(dX_k)} \tag{2}$$

A. *PHD Tracking of Vehicles*

The PHD is a function with peaks which identify the likely position of the targets. PHD is the first order moment of state of set. By integrating the PHD on any region R of the state space, the expected number of targets in region R at time k can be computed. The PHD of the set is described by D(*x*).

$$\text{Expected number of targets in R} = \int_R D(x)\,dx \tag{3}$$

Fig.2 (a)

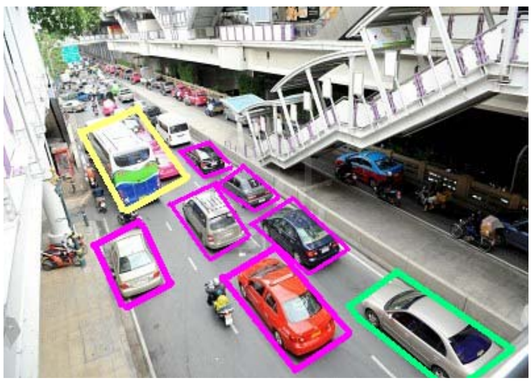

Fig. 2 (b)

Figure 2.

(a) The input image –still image, to the vehicle tracker

(b) Vehicles are identified and tracked using a rectangle, with purple indicating the identified vehicle, green represents the target birth and yellow to represent clutter event.

Vehicles are identified if the rectangle enclosing the target is greater than 5 ×5 pixels

B. Gaussian Mixture Model for learning

A simple solution to model birth and clutter events is to model by using Gaussian Mixture Model. The birth and clutter intensities are represented by *gb(x)* and *cl(z)*. They are given by equation

$gb(x) =$ Average Birth events/ frame

× probability distribution in state space

$cl(x) =$ Average clutter events/frame

×probability distribution in observation space

Probability distribution is obtained using GMM [12]. With the help of the equation (2), birth and clutter intensities can be computed. The same information is given as feedback so that the distribution of actual event is compared with prediction.

With the updated values of vehicle centroid, denoted by $\left(y^{(1)}, y^{(2)}\right)$. The size of the target or vehicle is obtained as *'l'* and '*b*'.

V. CONCLUSION

In this paper, an algorithm is proposed to track multiple vehicles, using PHD filter is enhanced by the use of Gaussian Mixture Model for birth and clutter events. PHD filter helps to spatially adapt the behavior of the target. As extension of this work, continuous learning can be adopted to improve the prediction behavior. Adaptive learning approach can also be implemented and such model should identify wrong distribution model chosen for birth and clutter intensities.

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REFERENCES

[1] H. Nguyen, Q. Ji, and A. Smeulders, "Spatio-temporal context for robust multitarget tracking," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 29, no.1, pp. 52-64, Jan. 2007.

[2] J. Vermaak, S. Godsill, and P. Perez, "Maonte Carlo filtering for multitarget tracking and data association," IEEE Transactions on Aerospace Electronics and Systems, vol. 41, pp. 309-332, 2005.

[3] Q.Yu, G. Medioni, and I.Cohen, "Multiple target tracking using spatio temporal markov chain Monte Carlo data association," in proceedings of IEEE Conference on Computer Vision and Pattern Recognition, June 2007, pp.1-8.

[4] D. Reid, "An algorithm for tracking multiple targets," IEEE Transactions on Automatic Control, Vol. AC-24, pp. 843-854, 1979.

[5] R. Mahler, "Multi- target Bayes filtering via first order multi-target moments," IEEE Transactions on AES, vol. 39, no.4, pp. 1152-1178, 2003.

[6] E.Maggio and A. Cavallaro, "Hybrid particle filter and mean shift tracker with adaptive transition model, " in Proceedings on Pattern Analysis and Machine Intelligence, vol. 18, no. 2, pp. 138-150, Feb 1996.

[7] I.J. Cox, and S.L. Hingorani, "An efficient implementation of Reid's multiple hypothesis tracking algorithm and its evaluation for the purpose of visual tracking," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 18, no.2, pp. 138-150 , Feb. 1996.

[8] H. Siden bladh, "Multi-target particle filtering for the Probability Hypothesis Density," in Proceedings of

International Conference on Information Fusion, Cairns, Australia, pp. 800-806, 2003.

[9] R. Mahler, “Random sets in information fusion: An overview,” in Random Sets: Theory and Applications, J. Goutsias et al. (eds.), Springer Verlag, pp. 129-164, 1997.

[10] M.Vihola, “Random sets for multitarget tracking and data association, “ Licentiate thesis, Department of Information Technology and Institute of Math., Tampere University, Finland, August 2004.

[11] Ba-Ngu Vo, and Wing-Kin Ma, “The Gaussian Mixture Probability Hypothesis Density filter, “ IEEE Transactions on Signal processing, vol. 54, no. 11, pp. 4091-4104, Nov. 2006.

[12] Emilio Maggio, and Andrea Cavallaro, “Learning scene context for multiple object tracking,” IEEE Transactions on Image Processing, vol. 18, no. 8, Aug. 2009.

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