Overlapping vehicle tracking via adaptive particle filter with multiple cues

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Ismail Saad
Universiti Malaysia Sabah (UMS)

Overlapping Vehicle Tracking via Adaptive Particle Filter with Multiple Cues

W.L. Khong, W.Y. Kow, Y.K. Chin, I. Saad, K.T.K. Teo
Modelling, Simulation and Computing Laboratory
School of Engineering and Information Technology
Universiti Malaysia Sabah
Kota Kinabalu, Malaysia
msclab@ums.edu.my, ktkteo@ieee.org

Abstract — **Vehicle tracking is a vital approach to assist the on-road traffic surveillance system. Since the on-road vehicles is increasing, occlusion and overlapping of vehicles is often happen in the traffic surveillance scene. Therefore, segmentation and tracking of the occlusion or overlapped vehicle can be a challenging task in surveillance system via image processing. In this paper, a multiple cues overlapping vehicle tracking algorithm is proposed to continuously track the occluded vehicle effectively. The earlier vehicle tracking systems are normally based on colour feature which will leads to inaccurate results when the background colour is complex or too similar with the target vehicle. On the other hand, shape feature will increase the accuracy but consume more computation time in the resampling process during overlapping. The experimental results show that enhancement of the particle filter resampling process with multiple cues is capable to track the overlapped vehicle with higher accuracy and without compromising the processing time.**

Keywords - vehicle tracking; particle filter; likelihood; multiple cues

I. INTRODUCTION

Vehicle tracking has drawn great attention among the researchers due to the wide range of its applications such as road traffic control, accident avoidance, navigation, traffic surveillance and security [1]. Researchers usually focus on the difficulty and complexity problems faced in vehicle tracking. For instance, occlusion and overlapping is one of the challenging tasks that often occurred in vehicle tracking due to the heavy traffic nowadays [2]. In this study, video sensor is chosen for the vehicle tracking purpose due to the rapid development of video surveillance infrastructure. Various information of the vehicle such as colour, shape, and speed of the vehicle can be provided through application of image processing technique on the captured video.

Literature review shows different techniques have been developed for vehicle tracking purpose. For example, Markov chain Monte Carlo, Kalman filter [3, 4], optical flow, particle filter are among the well known image processing method for object tracking purpose. Vehicle tracking in traffic flow consists of dynamic changes could be a non-linear situation. Although the extended Kalman filter has the ability to deal with the non-linear and non-Gaussian problem, it still consist the problem of diverge when nonlinearity is inaccurately approximated. Therefore in this study, particle filter is chosen as a more reliable tracking algorithm for vehicle tracking since it is a promising and powerful technique that can deal with non-linear and non-Gaussian problems [5].

In the past, many algorithms have been proposed for tracking purposed that rely on single feature. One of the commonly use feature is colour histogram. In research [6, 7], colour feature has been widely used as the only feature to track non-rigid objects and vehicle respectively. From the results, colour feature can be proven as a strong and influential parameter to deal with partial occlusion, scale invariant and rotation incidents. However, algorithm using colour feature have limitation where the background colour is complex or too similar with the target object.

In certain cases, colour feature alone provide insufficient information about the target object but multiple features allow more details are extracted to perform effective object tracking. Therefore the accuracy of the tracking performance can be increased by using multiple parameters. In research [8], colour and contour features has been study to track moving target accurately although occlusion happens. However, calculation for combine features is more complex and hence the processing speed is slow. When particle filter applied on visual tracking, the particle degeneracy problem will occur. Resampling is one of the solutions to avoid the particle degeneracy problem without using a huge amount of sample size [9]. Thus, an adaptive particle filter is proposed in this study where the particle samples are computed based on shape feature and resample using colour feature. The experiment results show that multiple cues algorithm is better in tracking overlapping vehicle with higher accuracy and without compromising the computational time.

The paper is organized as follow. In section II, the brief description of particle filter framework is introduced. Next, the algorithm to compute the likelihood will be presented. Section IV shows the justification of the need for resampling process. Section V introduces the proposed particle filter algorithm. Section VI reviews how vehicle being localized, while section VII presents and discusses the result obtained from the proposed algorithm. Finally, conclusions are presented.

II. PARTICLE FILTER FRAMEWORK

Particle filter also known as sequential Monte Carlo which is a mainstream algorithm for nonlinear and non-Gaussian Bayesian tracking based on Bayesian sequential sampling technique [10]. Particle filter algorithm is developed based on estimating the current state of the target object depending on the previous and current particle locations. For visual tracking purpose, the observation state of the target can be colour, edge, shape which are the information extracted from the target object. In this study, colour and shape have been chosen as the features for vehicle tracking purpose.

In general, dynamics changes in visual tracking consist of nonlinear and non-Gaussian elements. Therefore, the posterior probability density function (1) and the observation probability density function (2) in the particle filter algorithm are often non-Gaussian. The posterior probability density function can be obtained through the prediction and update stages recursively. Meanwhile, the observation probability density function expresses the likelihood of the feature that describes the model.

$$p(X_t \mid Z_t) \tag{1}$$

$$p(Z_t \mid X_t) \tag{2}$$

The state vector X_t denotes the quantities of the tracked object while Z_t denotes all the observations state at time t. In the prediction stage, the prior probability density function can be obtained through (3). After that, the posterior probability density function can be obtained through the updated stage using the Bayes' rule in (4).

$$p(X_t \mid Z_{1:t-1}) = \int p(X_t \mid X_{t-1}) p(X_{t-1} \mid Z_{1:t-1}) dX_{t-1} \tag{3}$$

$$p(X_t \mid Z_{1:t}) = \frac{p(Z_t \mid X_t) P(X_t \mid Z_{1:t-1})}{p(Z_t \mid Z_{1:t-1})} \tag{4}$$

In the particle filter algorithm, a set of N weighted particle samples represents the posterior probability density function from the prior density. Since the weighted random particles are in discrete nature, the posterior probability density function can be obtained through (5) where w_t^i is the normalized important weight as shown in (6).

$$p(X_t \mid Z_{1:t}) \approx \sum_{i=1}^{N} w_t^i \delta(X_t - X_t(i)) \tag{5}$$

$$w_t^i = w_{t-1}^i \frac{p(z_t \mid x_t^i) p(x_t^i \mid x_{t-1}^i)}{q(x_t \mid x_{1:t-1}, z_{1:t})} \tag{6}$$

In general, particle filter is operating based on three important steps which are generate the state transition of the model, compute the weight of the particles based on the likelihood estimation, and resampling. In the first step, a set of fixed number of particles has been initialized and each particle represents the estimated prior position of the model. The more particles or samples size will increase the tracking accuracy. However, the processing time will be increased and the efficiency of the tracking system will be reduced. After compute the prior position of the target model, the following step is to compute the weight of each particle based on the likelihood of the features. If the similarity of the features likelihood of the target vehicle and reference model is higher, the weight assigned to the particle will be heavier. Lastly, resampling process is an important step to avoid the particle degeneracy problem. Resampling can be used to eliminate the entire low weight particle and regenerate a new set of particle with higher weight to increase the accuracy of the tracking results.

III. LIKELIHOOD COMPUTATION

This section describes how the weight of the particles will be computed based on the features likelihood. Shape and colour features are chosen as the multiple cues to compute the weight of the particles based on the similarity histogram of the target vehicle and the reference vehicle model.

A. Colour Feature and Distribution Model

In this study, colour is the significant parameters used for vehicle tracking purpose. Colour is a promising feature that can be used to overcome the partially occlusion and scale invariant incidents. Besides, the processing time needed to obtain the information of the colour histogram is shorter comparing to other parameters. As a result, most of the visual tracking algorithms utilize colour feature as the likelihood parameter.

The colour information of the target vehicle is generated using RGB colour space to obtain a discrete 8 × 8 × 8 bins colour histogram. After obtaining the colour histogram, the weight of the particles will be generated based on the likelihood of the target vehicle and the reference vehicle. In order to calculate the similarity between the two colour histograms, Bhattacharyya coefficient is chosen.

Bhattacharyya coefficient is a common technique used to calculate the likelihood of the colour histogram between two colour distributions [11]. Bhattacharyya coefficient measures the coefficient among the colour histogram of the target and samples. Since the colour histogram is a discrete density model therefore the coefficient of the likelihood can be obtained through (7) where the colour histogram of the target vehicle is $p = \{p_u\}_{u=1 \ldots N_c}$ whereas the colour histogram of the reference vehicle is $q = \{q_u\}_{u=1 \ldots N_c}$. If both of the histograms are identical, the coefficient $\rho = 1$ will be set. From the coefficient obtained, the Bhattacharyya distance can be calculated through (8).

$$\rho[p,q] = \sum_{u=1}^{N_c} \sqrt{p_u q_u} \tag{7}$$

$$d_c = \sqrt{1-\rho[p,q]} \tag{8}$$

Based on the Bhattacharyya distance obtained, the weight of the particles can be calculated using (9) where σ is the adjustable standard deviation which can be chosen experimentally.

$$\varphi_c = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{d_c^2}{2\sigma^2}} \tag{9}$$

Therefore, the more similar of the colour of the reference vehicle to the colour of the estimated position of the target vehicle, the weight of the particle is heavier. This estimated position became the possible location of the target vehicle and updated in the measurement state of the particle filter algorithm.

B. Shape Feature and Distribution Model

Colour feature is reliable in most of the visual tracking algorithm even though during the occlusion incident. However, consider colour feature as single feature might cause problem when the background colour and colour of target vehicle have similar colour distribution. In addition, the complexity of the background colour also leads to an inaccurate tracking result. Hence, the shape of the vehicle is introduced to the algorithm to enhance the accuracy of the tracking performance. Shape is chosen instead of edge since shape feature can be more accurately differentiating the type of vehicles. Fig. 1 shows the shape of the extracted vehicle.

After the shape of the vehicle being extracted, the weight of the particles based on shape feature will be computed using Hausdorff distance. Hausdorff distance is a scalar measure of the distance between two sets of points which obtained from detecting the shape of the reference vehicle model and the target vehicle where $A = \{a_u\}_{u=1\ldots N_c}$ and $B = \{b_u\}_{u=1\ldots N_c}$ are two sets of points from the shape feature of the vehicle [12].

Next, the Hausdorff distance between two points set can be calculated based on (10) and (11). $||a - b||$ in (11) is the distance measure by Euclidean norm which it is sensitive to noise and occlusion.

$$H_{dist}(A,B) = \max(h(A,B), h(B,A)) \tag{10}$$

where

$$h(B,A) = \underset{b\in B}{K^{th}} \min_{a\in A} \|a-b\| \tag{11}$$

(a) (b)

Figure 1. Shape feature of vehicle.

$\underset{b\in B}{K^{th}}$ in (11) denotes the K^{th} ranked value in the set of distance computed. Based on the Hausdorff distance obtained, the weight of the particles can be updated using (12) where σ is the standard deviation which is adjustable. Although the shape feature can be used to describe the information of the vehicle, using shape feature alone will make the processing time for tracking very slow.

$$\varphi_s = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{H_{dist}^2}{2\sigma^2}} \tag{12}$$

IV. PARTICLE FILTER RESAMPLING

Particle filter is known as a good approach in visual tracking with non-linear and non-Gaussian problem. However, particles filter also facing the weakness of particle degeneracy after several iterations. In general, implementing large size of particle samples and resampling the particles can be used to avoid the particle degeneracy problems. Although both methods can increase the accuracy of the tracking results, resampling is more suitable because the computational time for resampling is much lesser than applying huge amount of the particle samples.

In order to check whether particle degeneracy problem occur or not, the effective sample size need to be calculated using (13) with the true weight. Since the true weight in (14) of the particle cannot be evaluated exactly, therefore an estimate of effective sample size can be computed through (15) where w_t^i is the normalized weight calculated using (6).

$$N_{eff} = \frac{N_s}{1+Var(w_t^{*i})} \tag{13}$$

where

$$w_t^{*i} = \frac{p(x_t^i \mid z_{1:t})}{q(x_t^i \mid x_{t-1}^i, z_t)} \tag{14}$$

$$\hat{N}_{eff} = \frac{1}{\sum_{i=1}^{N_s} (w_t^i)^2} \tag{15}$$

V. PROPOSED PARTICLE FILTER ALGORITHM

In order to track vehicle accurate and efficient, more features need to be implemented into the tracking algorithm. This is because with more features, more information that describes the target vehicle can be obtained. Tracking with multiple cues is helpful in continuously tracking process especially when the occlusion and overlapping incidents occurs. In this study, the shape and the colour features have been chosen as the multiple cues for tracking purpose.

Shape feature is chosen instead of edge feature because it can be more significantly describing the outlook of the vehicle. However, the time taken to process the shape feature is much longer than the colour feature. Although colour feature has shorter processing time, accuracy of the tracking will be affected if dealing with the complex background or the target vehicle colour is similar to the background colour.

In this proposed algorithm, the shape feature and colour feature will be calculated separately. With the purpose of shorten the computational time while increasing the accuracy of the tracking results, the proposed particle filter algorithm need to be adaptive. Therefore, adaptive particle filter using shape feature to separate the target vehicle and resampling using colour feature to stronger the estimated position of the target vehicle is proposed. The proposed particle filter tracking algorithm is shown in Table I.

VI. Position Localization

In this section, estimating the position of the target vehicle will be discussed. From Table I, the weight of the particles will be calculated based on the likelihood of the shape feature. If the particle degeneracy problem occurs, the lower weighted particles will be eliminated. Then, resampling using colour feature based on the higher weighted particles will be carried out. After resampling, the particles will be distributed to the center of the target vehicle. Finally, the location of the estimated target vehicle can be calculated through the mean coordinates generated by the particles.

VII. Result and Discussion

In this section, the results of vehicle tracking using single feature and multiple features are shown in Fig. 2, Fig. 3 and Fig. 4 respectively. Fig. 2 shows that the result of vehicle tracking algorithm using colour parameter. Fig. 3 shows the result of shape feature implemented into the tracking algorithm. Fig. 4 illustrates the result of the proposed vehicle tracking method using multiple cues. For all the cases, the particle size was initialized as 200 samples size.

Based on the results shown in Fig. 2, Fig. 3 and Fig. 4, the tracking was divided into four cases, namely ‘before occluded’, ‘partially occluded’, ‘fully occluded’ and ‘after occluded’. Referred to the sequence of results shown in Fig. 2, Fig. 3 and Fig. 4, the proposed particles filter algorithm has shown the higher accuracy in tracking the moving vehicle.

In case 1, it can be observed the moving vehicle before occlusion as shown in Frame 28. The single feature and multiple features can both track the moving vehicle accurately. This is because before occlusion occur, the information of the moving vehicle can be clearly obtained and without influenced by others obstacles.

Case 2 refer to the partially occluded moving vehicle. From the results shown in Fig. 2 and Fig. 3 at Frame 33, the tracker indicated a position which is not accurate for the moving vehicle. The accuracy of the tracking has been decreased due to the information of the moving vehicle is influenced by the static vehicle. However, with the proposed tracking algorithm, the moving vehicle can be accurately

TABLE I. Proposed Particle Filter Algorithm

Multiple Cues Particle Filter Tracking Algorithm

Initialize reference shape feature, reference colour histogram and sample size
FOR FRAME = 1, 2,…, t
PREDICTION:
FOR i = 1, 2,…, N_s
Draw predicted particles from prior dynamics
Compute the shape feature based on estimated position
END FOR
UPDATE:
Calculate the Hausdorff distance, H_{dist}
Compute the weight of the particle based on Hausdorff distance, φ_s
Normalize the weight, $w_t^i = w_t^i (\sum_{i=1}^{N} w_t^i)^{-1}$
Calculate $\hat{N}_{eff}$
IF $\hat{N}_{eff} < N_s$
Choose the highest weight of the particle
END IF
IF $w_t^i < w_{thres}$
Remain the strong particles and eliminate the weak particles
$M = M + 1$
END IF
RESAMPLING:
WHILE ($\hat{N}_{eff} < N_s$ && $M < N$)
FOR $i = M$-1, M,…, N
Compute the colour histogram based on estimated position
Calculate the Bhattacharyya distance, d_c
Compute the weight of the particle based on Bhattacharyya distance, φ_c
Normalize the weight, $w_t^i = w_t^i (\sum_{i=1}^{N} w_t^i)^{-1}$
Calculate $\hat{N}_{eff}$
IF $\hat{N}_{eff} < N_s$
Goto: Resampling
$M = M + 1$
END IF
END FOR
END WHILE
Calculate the estimated position
END FOR FRAME

located as shown in Frame 33 and Frame 42 at Fig. 4. With multiple cues, the tracker can gain more information of the moving vehicle. Since the proposed tracking algorithm is sampled with shape and resampled using colour feature, the computational time is lesser than the case of combined weight.

In case 3, the vehicle is fully occluded as shown in Frame 38 at Fig. 2, Fig. 3 and Fig. 4. When the moving vehicle is fully occluded, the information of the moving vehicle will be lost. Thus, the tracker will continuously to search for the possible location of the moving vehicle.

In case 4, the moving vehicle after occlusion is shown in Frame 45. From the result obtained in Fig. 2, Fig.3 and Fig.4, only the proposed algorithm with multiple cues accurately estimated the position of the moving vehicle. When occlusion occurs, the information of the moving vehicle will be influenced by the obstacle or static vehicle. Therefore, with single feature algorithm as shown in Fig. 2 and Fig. 3, more time will be needed to recover the tracking of the moving vehicle while it is totally lost track. However, with the proposed particle filter algorithm, the moving vehicle can be located immediately after occlusion occurred as the result shown in Frame 45 in Fig. 4.

Fig. 5 shows the graph of root mean square error (RMSE) versus frame index. From the result shown, the proposed multiple cues particle filter which initiate with shape feature followed by resampling colour feature has a more accurate tracking results compared to single feature used.

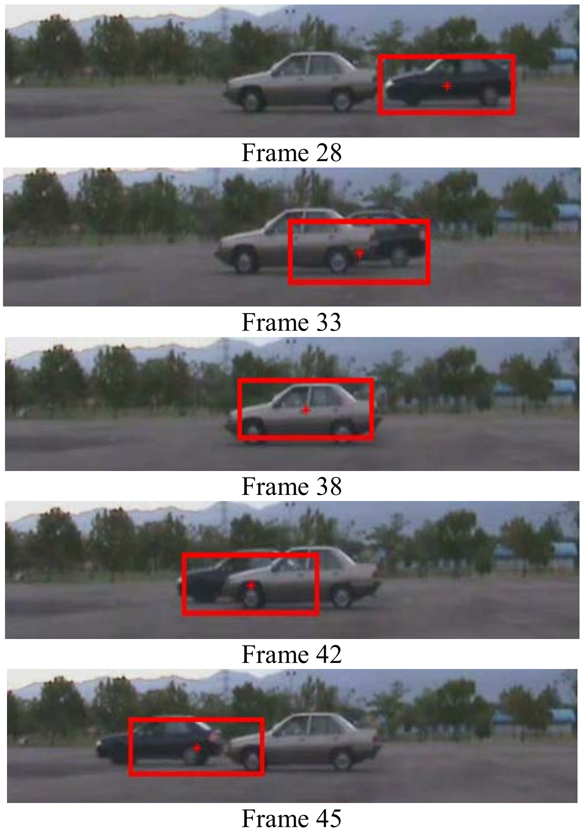

Figure 2. Result of vehicle tracking by using colour feature only.

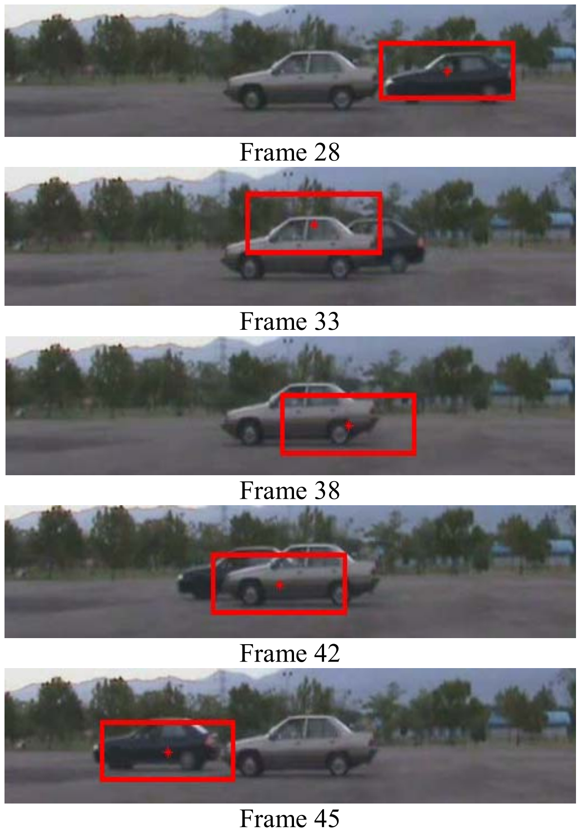

Figure 3. Result of vehicle tracking by using shape feature only.

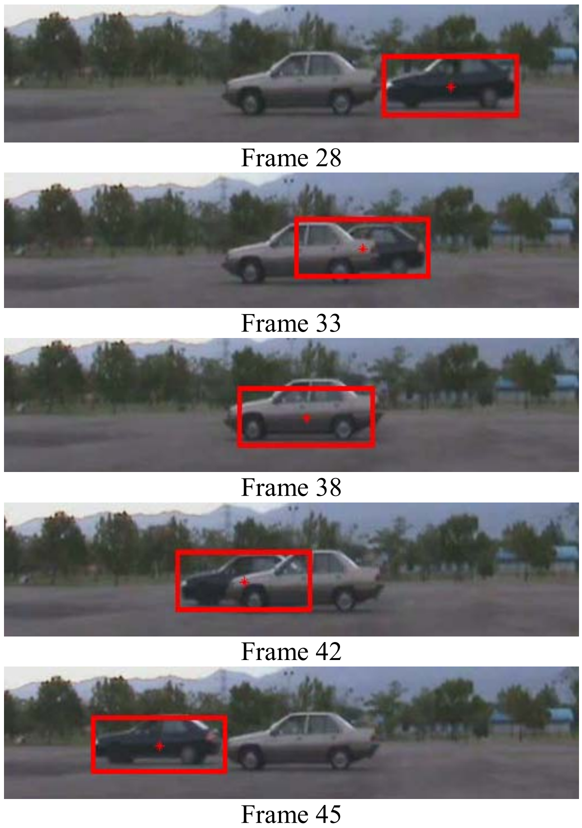

Figure 4. Result of vehicle tracking by proposed multiple cues tracking algorithm.

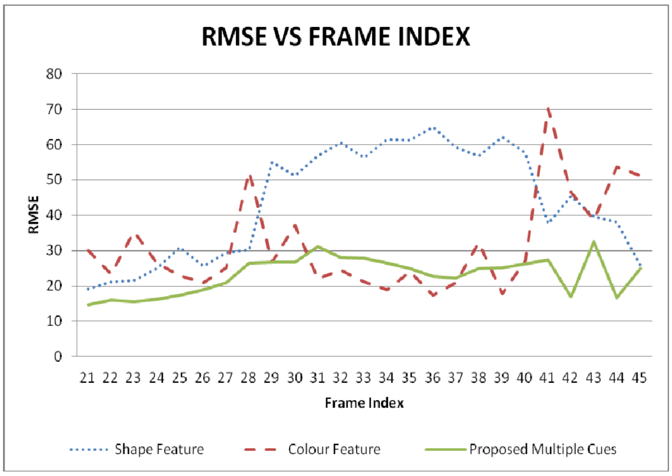

Figure 5. Graph of RMSE vs frame index.

VIII. CONCLUSION

In this paper, an adaptive particle filter algorithm initiated with the shape feature and followed by resampling with colour feature has been proposed for continuously tracking overlapping moving vehicle. Tracking algorithm with multiple cues shown a promising result since more information describes the vehicle can be obtained from the experiments. Besides, due to the reason of longer processing time needed to process shape feature, the likelihood of the particle in the proposed algorithm separated the shape feature and colour feature instead of combining the likelihood of the both features. Having more particle samples usually increase the accuracy of the tracking performance but consume more computational cost. Based on the results shown in this work, the proposed algorithm with multiple cues is capable of dealing with the efficiency and effectiveness of the tracking performance.

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