Overlapped Vehicle Tracking via Enhancement of Particle Filter with Adaptive Resampling Algorithm

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Abstract **- Traffic surveillance and on-road security have elevated the demand of machine vision aided traffic control system. Through the modern video camera technology, vehicle tracking has become a vital approach to assist the on-road traffic systems. In the past, many tracking methods have been developed based on the detail and information extracted from the captured vehicle. However, conventional tracking system need to be improved since the background noises and sudden appear objects will increase the difficulties of continuously tracking the target vehicle. Hence, a particle filter algorithm with adaptive resampling approach has been proposed to overcome the vehicle occlusion problems. In addition, the proposed resampling approach can also be used to solve the common particle degeneracy problem. Experimental results show that the enhanced particle filter equipped with adaptive resampling algorithm is significantly improving the accuracy of the tracking process without compromising the processing time.**

Keywords - particle filter, adaptive re-sampling, vehicle tracking, traffic surveillance

I. INTRODUCTION

Vehicle tracking is an essential approach that has drawn the attention among the researchers due to its numerous fields of applications such as road traffic control system, traffic surveillance and security system [1]. However, occlusion and overlapping between vehicles is a challenging task in surveillance system via image processing. Due to the difficulties and complexity caused by the occlusion problems, the researchers are incited to study the effective and efficient vehicle tracking method. In this research, video sensor is chosen as the tracking infrastructure rather than others sensors because of the rapid development in video camera technology. Furthermore, a wide range of the information to describe the target vehicle such as the colour, motion, edge, shape and speed of the vehicle can be extracted from the video sensor via image processing techniques.

Alternatively, vehicle flow consists of dynamic changes which could lead to non-linear and non-Gaussian conditions. Hence, particle filter has been chosen as the vehicle tracking algorithm in this research due to its ability to overcome the non-linear and non-Gaussian situations. Nevertheless, particle degeneracy was the main factor that will influence the accuracy of vehicle tracking results. Therefore, an efficient and effective resampling approach will be needed to solve the common particle degeneracy problem. Thus, an enhancement of the particle filter with the adaptive resampling step is implemented to continuously tracking the target vehicle under various overlapping incidents without compromising the processing time.

II. REVIEWS OF OBJECT TRACKING

In the past, many methods have been developed for object tracking purpose. Among the well known techniques of image processing tracking methods are Markov chain Monte Carlo [2], Kalman filter [3, 4], optical flow and particle filter [5, 6, 7]. Vehicle flow consists of dynamic changes may lead to non-linear and non-Gaussian situation. In this case, the development of extended version of Kalman filter can be used to overcome the non-linear situation. However, when the nonlinearity is inaccurately approximated by the extended Kalman filter technique, the estimated results will be diverging and hence lead to an inaccurate tracking result. Particle filter is proven as a promising and powerful technique to overcome the non-linear and non-Gaussian situation. It has been chosen as the overlapped vehicle tracking technique due to its ability to cope with the non-linear and non-Gaussian state [8, 9].

In research [10], the non-rigid objects have been tracked by using the colour feature. It is suggested that the algorithm selected for object tracking purpose should be able to deal with the partial occlusion and scale invariant incidents. Nevertheless, colour is a powerful feature that can be implemented in these situations. The extracted colour histogram of the target vehicle will be comparing with the colour histogram of the sample vehicle by using Bhattacharyya distance. As discussed in [10], the colour based algorithm can efficiently handle the non-rigid and fast moving objects under different conditions.

According to reference [11], the typical particle filter will face a phenomenon named as particle degeneracy during the tracking process. Particle filter degeneracy occurs due to the low weight or weak particle is selected after several iterations and it blocks the further improvement of the algorithm. In general, there are two ways used in solving the particle degeneracy problem. The solution is either increasing the number of particle size implemented in the algorithm or resampling the particles. However, increase the particle size is insufficient due to the huge amount of the sample size could lead to higher computational complexity and processing time. On the other hand, resampling can increase the accuracy of the tracking results by eliminating the low weight particles and regenerate with strong weight particles without compromising the processing time [12].

As mentioned in [13], occlusion and sudden appear objects incident are among the challenging tasks that will be faced in vehicle tracking. Therefore, the proposed particle filter algorithm must be robust whether in the partially or fully occlusion incidents. When the target object is being overlapped, the information of the target object will be vanished or influenced by the obstacle. The tracking performance based on the results is accurate but the algorithm fails when there is a large degree of disjoint during the tracking.

III. METHODOLOGY

This section discusses the methodology of the particle filter and explains the likelihood of the samples being computed.

A. *Particle Filter Framework*

In this section, a brief review of particle filter will be presented. Particle filters also known as sequential Monte Carlo which is an iterative process that estimates posterior distribution from a finite set of weighted particles [14]. It is developed based on estimating the current state of the target vehicle from the previous particle set. Basically, the conventional particle filter algorithm consists of three important steps which are prediction stage, measurement stage and resampling stage.

In the prediction stage, the particle filter will generate a new particles set with each particle represents the estimated posterior position. The increment of the number of particles can improve the accuracy of the estimation. Meanwhile, the computational time will be longer with the large amount of the particle size.

In the measurement stage, each particle weight is computed based on likelihood probability. For visual tracking purpose, the observation state of the target vehicle can be colour, edge or shape that extracted from the information of the target vehicle. In this study, colour feature has been selected as the parameter for the vehicle tracking.

The third stage refers to the resampling process. Resampling is an important step to reduce the particle degeneracy problems. Particle degeneracy affects the accuracy of the tracking results. During particle degeneracy, the low weight particle is continually selected and used by the particle filter algorithm which leads to inaccuracy results. Hence, resampling algorithm is needed to eliminate the low weight particle and regenerate a new set of particles until the particle sets with large weight is obtained. It is important to avoid the particle degeneracy problem to improve the accuracy of the tracking results.

The dynamic changes in vehicle tracking usually consist of nonlinear and non-Gaussian elements. The posterior probability density function as described in (1) can be obtained through the prediction stage. However, the observation probability density function as in (2) is used to express the likelihood of the colour feature.

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

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

The quantities of the tracked object is denotes by state vector X_t while all the observations state at time t is denotes by vector Z_t. In the prediction stage, the prior probability density function can be obtained through (3) and the posterior probability density function is defined 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, the posterior probability density function developed from the prior density is represented by a set of N weighted particle samples. Meanwhile, posterior density function can be obtained through (5) because the weighted particles are in discrete nature and w_t^i is the normalized weight as shown in (6).

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

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

B. *Color Distribution Model*

In this research, colour feature has been chosen for the vehicle tracking purpose because of its ability to deal with the partial occlusion and scale invariant problems. Moreover, the processing time to obtain the colour information of the target vehicle is much faster than other parameters. Hence, colour feature has been chosen and implemented in most of the visual tracker.

The colour histogram of the target vehicle is normally calculated in the RGB colour space to obtain a discrete 8 × 8 × 8 bins histogram. After obtaining the colour histogram of the target vehicle, it will be compared with the colour histogram of the reference vehicle in order to compute the similarity of the two histograms which is called likelihood. Bhattacharyya distance is a common technique used to measure the likelihood between two colour histograms. After the obtaining the Bhattacharyya distance, the weight of the particle can be calculated based on the likelihood.

C. Bhattacharyya Distance

Generally, the measurement between two colour distribution histogram is calculated by the common technique called Bhattacharyya coefficient [15]. In this case, the Bhattacharyya coefficient is used to calculate the coefficient between colour histogram of reference vehicle, $p = \{p_u\}_{u=1...N_c}$ and colour histogram of the target vehicle, $q = \{q_u\}_{u=1...N_c}$ as shown in (7).

$$\rho[p,q] = \int \sqrt{p_u q_u}\, du \tag{7}$$

Since the colour histogram is a discrete density model, the Bhattacharyya coefficient can be obtained through (8).

$$\rho[p,q] = \sum_{u=1}^{N_c} \sqrt{p_u q_u} \tag{8}$$

The value of Bhattacharyya coefficient represents the similarities of two colour distribution. The larger value of the coefficient means more similarity in the colour distribution. However, the limit of the coefficient is set from 0 to 1. If both the histogram is identical, then the coefficient will be indicated as 1.

After obtaining the Bhattacharyya coefficient, the Bhattacharyya distance can be computed using (9).

$$b_{dist} = \sqrt{1 - \rho[p,q]} \tag{9}$$

Based on the Bhattacharyya distance, the weight of the particles can be calculated using (10) where σ is the adjustable standard deviation which can be chosen experimentally.

$$\varphi_c = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{{b_{dist}}^2}{2\sigma^2}} \tag{10}$$

The weight of the particles is set to heavy when the colour of the reference vehicle and the colour of the target vehicle are too similar. This estimated position represented by the heavy particle will become the possible location of the target vehicle and it will be updated in the measurement stage of the particle filter algorithm.

IV. RESAMPLING ALGORITHM

As discussed in the previous section, resampling process is needed to eliminate the particle degeneracy problem. This section will describe the particle degeneracy in more detail. Then the conventional resampling and proposed resampling algorithms are discussed towards the particle degeneracy situation.

A. Particle Degeneracy

Particle filter is a good approach in vehicle tracking due to the ability to deal with non-linear and non-Gaussian situations. However, after several iterations, the particle filters also facing the problem caused by particle degeneracy. Generally, implementing the particle filter algorithm with large size of particle samples or resampling the particle samples is capable of avoiding the particle degeneracy problem. Although both approaches can be used to improve the accuracy of the vehicle tracking, resampling is more suitable to be implemented into the particle filter algorithm. Resampling is chosen since the computational time is much lesser compared to applying huge number of particles.

In order to measure the appearance of the particle degeneracy problem, the effective sample sizes need to be calculated using (11). Since, the true weight of particles in (12) cannot be determined, an estimate of the effective sample size will be computed using (13).

$$N_{eff} = \frac{N_s}{1 + Var(w_t^{*i})} \tag{11}$$

where

$$w_t^{*i} = \frac{p(x_t^i \mid z_{1:t})}{q(x_t^i \mid x_{t-1}^i, z_t)} \tag{12}$$

$$\hat{N}_{eff} = \frac{1}{\sum_{i=1}^{N_s} (w_t^i)^2} \tag{13}$$

The w_t^i in (13) is calculated using (6) and it is the normalized weight of each particle. After obtaining the estimated effective sample size, (13) is used to indicate whether particle degeneracy problem occurs or not.

If $\hat{N}_{eff} < N_s$, the particle degeneracy problem has occurred and resampling is needed. The particle filter will keep on recursively resampling until the requirement is reached.

B. Conventional Resampling

Resampling is commonly used to overcome the particle degeneracy problem. In the past, various type of resampling algorithm has been developed. The most common resampling algorithms being used to reduce the particle degeneracy are multinomial resampling, residue resampling, systematic resampling and stratified resampling.

In Table I, $\hat{N}_{eff}$ is the estimated effective sample size which is used to determine whether the particle degeneracy occurs or not. When the particle degeneracy occurs during the vehicle tracking process, the estimated effective sample size will be less than the initiated sample size. As a result, resampling will be activated and a new set of particle samples is regenerated. The newly generated particle samples will be reweighted via the colour likelihood technique. If the new set of the particle samples is not able to reach the threshold of the effective sample size, the resampling process is then continually being evaluated until the requirement is fulfilled.

When the overlapping vehicle is tracked by using the traditional resampling algorithm, the tracking results will not be promising. This is because when the target vehicle is being occluded by the obstacle, the information that can be extracted by particle filter will be limited. Therefore, more iteration of resampling algorithm is needed to obtain an accurate tracking result. However, after a few iteration of resampling process, the information of the vehicle will be influenced by the obstacle and hence the target vehicle will be lost track. Besides that, more computation time is consumed if the particle filter is recursively repeating the resampling stage due to the dissimilarity colour histogram of the reference vehicle and the colour histogram of the target vehicle.

C. Proposed Resampling

In this study, an enhanced particle filter algorithm with the adaptive function of resampling is proposed. With the proposed resampling algorithm, the resampling computational time will be optimized in vehicle tracking under various overlapping conditions. The enhanced resampling approach only resamples the low weight particles where the weight is below the threshold value. Meanwhile, the particles with the accepted weight will be stored as the reference position for vehicle tracking purpose. This is to shorten the resampling process and hence reduce the computational time with a promising vehicle tracking results. In short, it is suitable to be used when the vehicle is without occlusion or overlapping.

TABLE I. CONVENTIONAL RESAMPLING ALGORITHM

PF with Conventional Resampling Algorithm
Initialize 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 colour histogram based on estimated position
END FOR
MEASUREMENT:
Calculate the Bhattacharyya distance, b_{dist}
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 $\hat{N}_{eff}$
WHILE $\hat{N}_{eff} < N_s$
RESAMPLING:
Resample the discrete distribution
Generate new set of particles
Compute the weight of the particle based on Bhattacharyya distance, φ_c
Check the effective sample size
END WHILE
OUTPUT:
Obtain the position of the target vehicle
END FOR FRAME

However, when the target vehicle is being occluded, the information extracted by the particle filter algorithm might be incorrect and hence it might wrongly track the target vehicle due to lack of resampling process. Thus, during the occlusion, only the largest weight of the particle will be reserved for resampling purpose. Based on the largest weight of the particle, it is fast to track the target vehicle even only a small portion of the vehicle's color is visible.

Moreover, the proposed resampling algorithm can also assist in gaining back the information of the target vehicle faster than other resampling algorithm. The enhanced resampling algorithm for vehicle tracking is shown in Table II. Meanwhile, the flowchart of the particle filter with the adaptive resampling algorithm is illustrated in Fig. 1.

V. TARGET LOCALIZATION

In this section, estimation of the location for the target vehicle will be discussed. After the entire particles are weighted by the likelihood, the particle filter algorithm will

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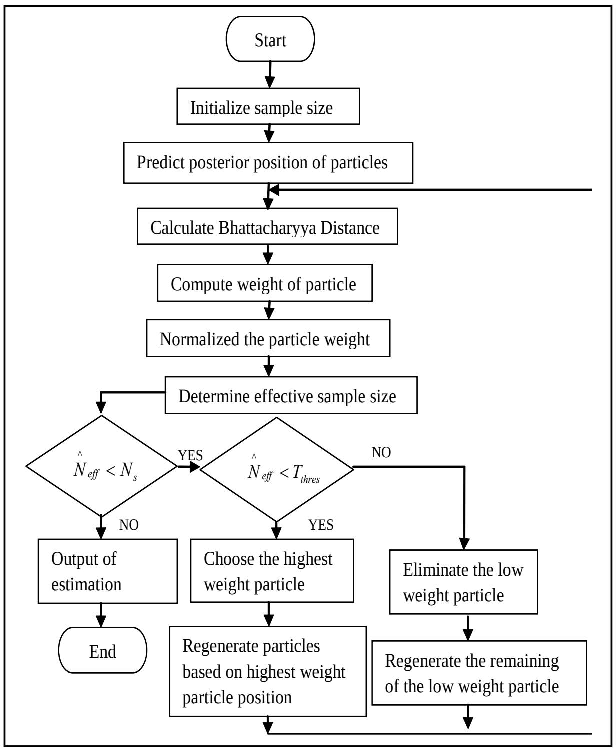

Figure 1. Flowchart of particle filter with adaptive resampling algorithm.

determine the needs of the resampling step. If resampling step is executed, the algorithm will check for the occlusion incident via the threshold. When the estimated effective sample size is lower than the threshold, the target vehicle is partially occluded or fully occluded. Hence, the highest weight of the particle will be remained as the reference position for the next prediction step while eliminating others particles. This action can speed up the algorithm to gain back the information of the target vehicle when there are a small portion colour of the target vehicle is visible.

On the other hand, when the estimated effective sample size is higher value than the threshold, the target vehicle is not occluded. Thus, in the resampling step, the particle filter only eliminate the low weight particle and at the same time the heavy weight particle will be remained. After that, the number of eliminated particle will be resampled and this step is repeating until the estimated effective sample size fulfils the requirements. The enhanced resampling process shortens the computational time compared to the conventional resampling algorithm because it only resamples the particles which potentially cause the degeneracy problem.

After resampling, output stage exists as the estimated position of the target vehicle. The position of the target vehicle can be easily calculated through the mean of all the coordination generated by the particles. This is because after the resampling stage, all the particles will be focused and concentrated at the centre of the target vehicle.

TABLE II. ADAPTIVE RESAMPLING ALGORITHM

PF with Adaptive Resampling Algorithm

Initialize 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 colour histogram based on estimated position
  END FOR
MEASUREMENT:
    Calculate the Bhattacharyya distance, b_{dist}
    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 $\hat{N}_{eff}$
WHILE $\hat{N}_{eff} < N_s$
RESAMPLING:
IF $\hat{N}_{eff} < T_{thres}$
    Choose the highest weight of the particle
    Resample the discrete distribution based on highest weight particle
ELSE
    Eliminate all low weight particles and remain the good particle
    Regenerate the remaining of the particles
END ELSE
    Compute the weight of the particle based on Bhattacharyya distance, φ_c
    Check the effective sample size
END WHILE
OUTPUT:
    Obtain the position of the target vehicle
END FOR FRAME

VI. RESULTS AND DISCUSSIONS

In this section, the results of vehicle tracking using the conventional particle filter resampling algorithm as shown in Fig. 2 will be compared to the results of vehicle tracking using an enhanced particle filter resampling algorithm as shown in Fig. 3. In both resampling algorithm, the particle size is initialized as 200 samples. Colour histogram is selected as the parameter to calculate the weight of the particles. A colour histogram with 8 × 8 × 8 bins RGB colour space will be computed. In this study, the colour feature has been chosen due to its ability to identify the target vehicle identity during partial occlusion. In addition, when there are a small portion of the colour of the target vehicle is visible, the enhanced particle filter algorithm is able to locate the target vehicle. Since colour histogram in discrete form, the time required to process will be short.

Based on the results shown in Fig. 2 and Fig. 3, the crossing icon represents the location estimated by the particle filter algorithm. Meanwhile the solid box refers the bounding box of the target vehicle. The target vehicle position is determined by calculating the mean value of the coordinates estimated by each particle.

Referring to Fig. 2 and Fig. 3, it can be observed that the tracking results can be divided into four cases which are 'before occluded', 'partially occluded', 'fully occluded' and 'after occluded'. Comparing to the results shown in Fig. 2 and Fig. 3, it can be noticed that the results obtained by using the particle filter with adaptive resampling algorithm is much more promising.

In Case I, the target vehicle is not occluded by another static vehicle as shown in Frame 5 of Fig. 2 and Fig. 3. Based on the results, the conventional and enhanced particle filter resampling algorithms are able to track the target vehicle. This is because before the occlusion, the information of the target vehicle can be easily obtained without influences by another vehicle. Thus, the particle filter resamples as usual by eliminating the weak particles and replacing those unwanted particles with a new set of particles.

In Case II, the target vehicle is partially occluded by the static vehicle as shown in Frame 13 of Fig. 2 and Fig. 3. From the result shown, it is noticed that colour is an important feature that can be used to deal with partially occlusion incidents. In this case, the resampling algorithm is executed as the previous case because the information of the target vehicle still obtainable and not influenced by the static vehicle. Thus, the target vehicle is able to be tracked with both resampling algorithms.

In Case III, the target vehicle is almost fully occluded by the static vehicle as shown in Frame 16 of Fig. 2 and Fig. 3. Most of the information of the target vehicle is either lost or influenced by the information obtained for the static vehicle. Thus, the conventional resampling algorithm is failed to locate the target vehicle because the particles has been trapped at the static vehicle by getting the wrong information. Meanwhile, the improved resampling algorithm is able to track the target vehicle although only a small portion of the target vehicle colour is recognized.

In Case IV, the target vehicle occurs after the occlusion as shown in Frame 25 of Fig. 2 and Fig. 3. Based on the results obtained, the conventional resampling algorithm is unable to track the target vehicle. The conventional resampling algorithm failed in tracking the vehicle after occlusion is because the information of the target vehicle has been lost and replaced by the information of the static vehicle. Therefore, the target vehicle is considered lost track by using the conventional particle filter algorithm as

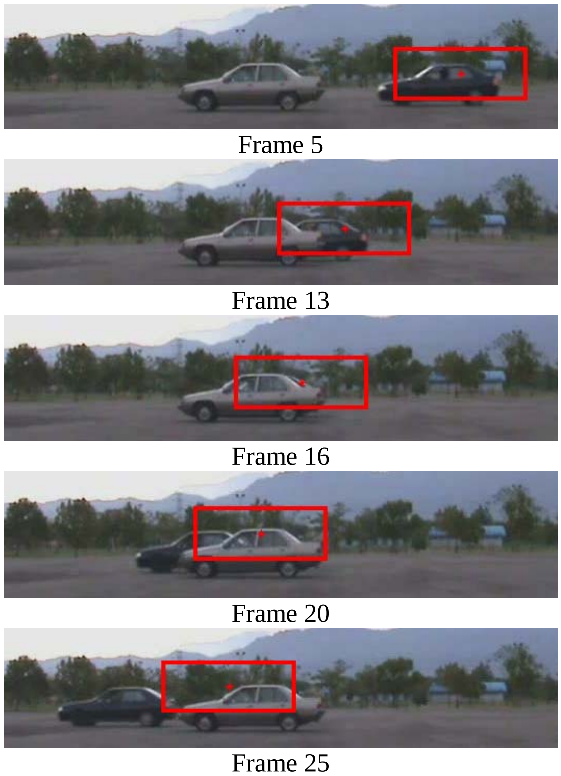

Figure 2. Results of vehicle tracking by using conventional resampling particle filter.

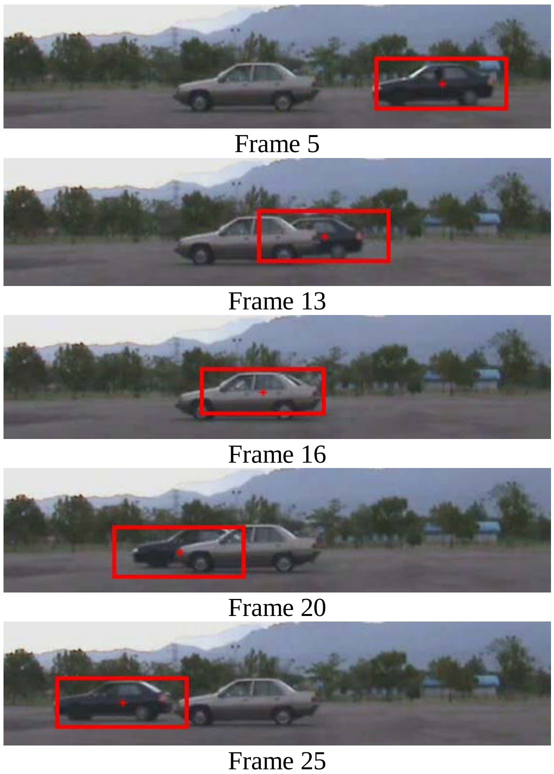

Figure 3. Results of vehicle tracking by using adaptive resampling particle filter.

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shown in Frame 25 of Fig. 2. However, the enhanced particle filter with adaptive resampling is able to continuously track the target vehicle as shown in Frame 25 of Fig. 3. Although the information of the target vehicle will be influenced by the static vehicle after the overlapping, the improved resampling algorithm is capable of remaining the location of the highest weight particle. A new set of samples will be generated to gain back the information of the target vehicle. Hence, the target vehicle is able to be continuously tracked by the proposed algorithm effectively and efficiently.

Fig. 4 and Fig. 5 show the RMSE and the resampling process as well as the sample size versus the frame index. Based on Fig. 4 and Fig. 5, the frame index of 1 to 10 indicates the target vehicle is free from occlusion. The results shows that both of the resampling algorithms are able to track the target vehicle due to the low value of RMSE. However, in terms of computational time, the adaptive resampling is faster than the conventional resampling as shown in Fig. 5 due to the lesser resampling steps and number of resampling particles .

During the frame index of 11 to 14, the target vehicle is partially occluded by the static vehicle. From the result shown in Fig. 4, the RMSE for both resampling algorithms are almost the same. After frame index of 14, the number of resampled particles has been increased due to the influeces from the static vehicle as shown in Fig. 5. Frame index of 16 shows that the target vehicle is fully occluded by the static vehicle. From Fig. 4, the RMSE for the conventional algorithm is much more higher than the proposed algorithm. This is because the information of the target vehicle is influenced by the static vehicle and causes the conventional algorithm to an inaccurate result. Meanwhile, the tracking result for the enhanced resampling algorithm is still promising with the low value of RMSE. In addition, Fig. 5 shows that the conventional algorithm will keep on resampling to locate the target vehicle and become an infinity loop. Thus, a maximum of 20 resampling steps has been set in order to terminate the infinity loop.

Frame index of 20 to 25 indicates the target vehicle is occurred after the occlusion. From the results shown in Fig. 4, the RMSE of the conventional algorithm is increasing due to the algorithm is still stuck at the static vehicle. The increasing of the RMSE means that the particle filter has diverged from tracking the target vehicle. However, RMSE for the enhanced algorithm is still remain at low level which means the visual tracker is still continuosly track the target vehicle. On the other hand, the number of resampling steps required for tha adaptive algorithm is still maintain at a low level. This means the adaptive algorithm can gain back the information of the target vehicle during and after the overlapping. However, the conventional algorithm is failed in tracking the target vehicle even though with the maximum of the resampling steps as shown in Fig. 5. The computational time taken by the adaptive algorithm is shorter than the conventional algorithm due to the number of resampling steps and resampled particle sizes is lesser.

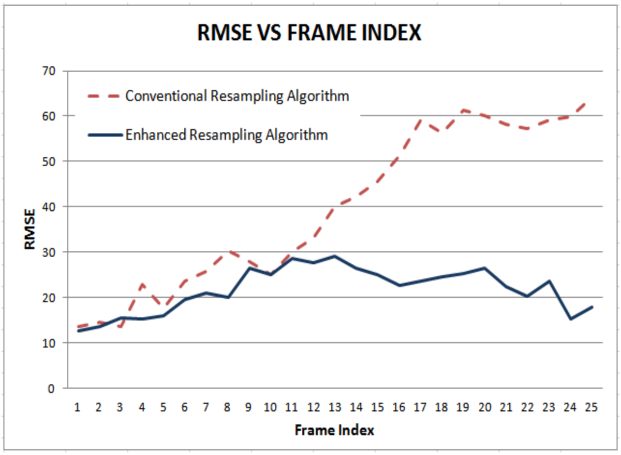

Figure 4. Graph of RMSE vs frame index.

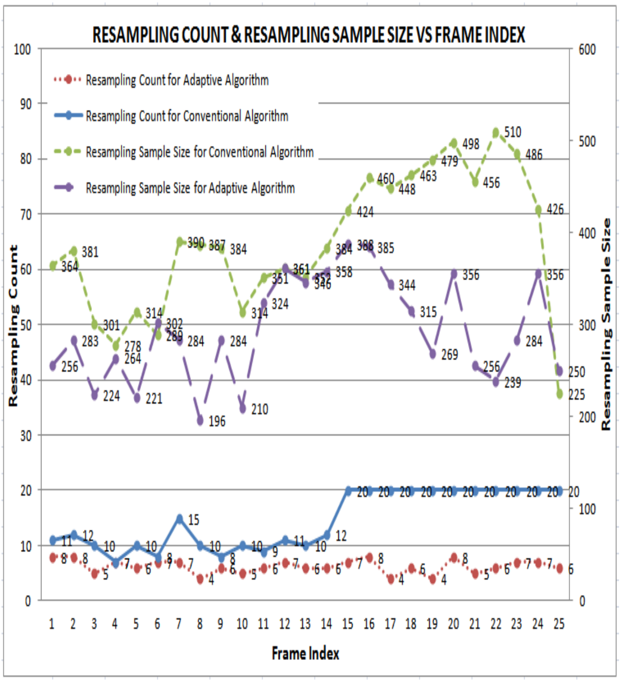

Figure 5. Graph of resampling count and resampling sample size vs frame index.

VII. CONCLUSION

As discussed in the previous sections, the accuracy of the particle filter algorithm will be diminished by the particle degeneracy. Conceptually, resampling can be used to avoid the particle degeneracy problem. Thus, an enhancement of the particle filter with adaptive resampling algorithm has been proposed for the purpose of tracking the overlapped vehicle. The implementation of the adaptive algorithm in the particle filter approach is capable to ease the tracking difficulties of various occlusion incidents. The performance and robustness of the proposed algorithm is tested and assessed under various tracking conditions. It can be concluded that the adaptive resampling approach has improved the accuracy of the tracking results without compromising the computational time.

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