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Enhancement of Particle Filter Approach for Vehicle Tracking via Adaptive Resampling Algorithm

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***Abstract* — Nowadays, vehicle tracking is a vital approach to assist and improve the road traffic control, surveillance and security systems by having the detail of the captured vehicle information. In past, many tracking techniques have been implemented and suffered from the well known 'occlusion' problems. Increasing the accuracy of the tracking algorithm has caused the computational cost due to the inflexibility to adapt the partial and fully occluded situations. Besides occlusion, appearance of new objects and background noises in the captured videos increase the difficulties of continuously tracking the labelled vehicles. In this paper, an adaptive particle filter approach has been proposed as the tracking algorithm to solve the vehicle occlusion problem. In order to solve the common particle filter degeneracy problem, the proposed particle filter is equipped with the adaptive resampling algorithm which is capable of dealing with various occlusion incidents. The experimental results show that enhancement of the particle filter via resampling algorithm has been robustly tracking the vehicles, and significantly improve the accuracy in tracking the occluded vehicles without compromising the processing time.**

Keywords - Vehicle tracking; Particle filter; Likelihood; Resampling

I. INTRODUCTION

In recent times, the number of the on-road vehicles has been obviously increasing. As the users of the vehicle increases, the incident such as accident that created by the vehicle user are also elevated. Therefore, the demand of the traffic monitoring system has incited researchers to study the vehicle tracking method in order to develop a complete system of road traffic control, surveillance and security by tracking the vehicle information. Today, many places have implemented video camera instead of using sensor for traffic monitoring purpose due to the development of video surveillance infrastructure. Many type of vehicle information such as velocity of the vehicle, license plate of the vehicle, kind of the vehicle and vehicle flow can be easily obtained through image processing method. Hence, vehicle tracking has been an active field of research in order to improve the road traffic control, surveillance and security system.

There are various techniques developed for vehicle tracking purpose. For example, Kalman filter [1, 2], optical flow, Markov Chain Monte Carlo are the well known method been using nowadays. Particle filter is a powerful technique in dealing with the non-linear and non-Gaussian problems [3]. Therefore, it is chosen as the study technique for vehicle tracking in this paper.

During the visual tracking process, there might be some of the weak or low weight particle which will block the further improvement of the algorithm. This phenomenon is addressed as particle degeneracy. Particle degeneracy is the essential problem faced when particle filter applied on visual tracking [4]. Therefore, resampling is the solution to overcome the particle degeneracy problem by eliminating the weak particle and regenerate a new set of strong weight particle [5]. Hence, resampling is an important step for a particle filter algorithm to increase the accuracy of the vehicle tracking.

Since the traffic flow nowadays is getting saturated, the vehicle might be occluded by other object from the video captured by the surveillance system. Therefore, in order to improve the applicability of particle filtering in vehicle tracking, its algorithm must be robust to partially or fully occlusion. Occlusion is a difficult task for the continuously vehicle tracking purpose [6]. When the target object is being occluded, the data of the target object will be lost. Therefore, more resampling step will be needed to obtain the vehicle information. Subsequently, if the vehicle information failed to recover after several repeated resampling steps, the visual tracker is going to lose track on the target object. Therefore, an adaptive resampling algorithm is introduced into particle filter to efficiently gain back the information of the target vehicle and continuously track the vehicle under various occlusion incidents.

The paper is organized as follows. In section II, the description of particle filter is briefly introduced. In the following section, the method of obtaining the color distribution model will be presented. In section IV, a Bhattacharyya coefficient method is introduced in order to calculate the likelihood. Section V shows the method of localizing. Section VI discusses the cause of particle degeneracy and resampling algorithm, while section VII presents and discusses the result obtained from the methods. At the end of the paper, conclusions are presented.

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II. PARTICLE FILTER

Particle Filter also known as sequential Monte Carlo which is an important Bayesian sequential sampling technique [7]. It is recursively approximating the posterior distribution using weighted samples. Particle filter normally consists of three important steps. First step is to generate new particles with each particle represents the estimated posterior position. The accuracy of the estimation is improving with the increasing of the number of particles. Unfortunately increasing the particle sample size with more particles caused the computational time to be longer.

Second step is to compute each particle weight based on likelihood. In this study, the color likelihood will be used as the parameter for vehicle tracking. The particle will be weighing based on the similarity of the color histogram of the reference target with the sample target. The more similar of the color histogram, the particle will be assigning more weight.

Third step refer to the resampling part. In common, particle degeneracy is the main problem faced when particle filter applied to visual tracking. The resampling part is able to eliminate the weak particle and regenerate the particle with the largest weight so that more accuracy of the tracking result can be obtained.

Generally, particle filtering is introduced to track objects in which the posterior density $p(X_t \mid Z_t)$ and the observation density $p(Z_t \mid X_t)$ are often non-Gaussian. The vector X_t refer to the quantities of tracked object while Z_t denotes the observations up to time t. Therefore, at time t, the state can be updated using Bayes' rule in (1)

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

The posterior $p(X_t \mid Z_{1:t})$ is estimated by a finite set of N samples with important weights w_t^i. The weights of the samples show in (2)

$$w_t^i = w_{t-1}^i \frac{p(z_t \mid x_t^i)p(x_t^i \mid x_{t-1}^i)}{q(x_t \mid x_{1:t-1}, z_{1:t})} \quad (2)$$

III. COLOR DISTRIBUTION MODEL

In this research, color has been chosen as the parameter for vehicle tracking. Color is an important parameter that can be used for tracking objects that are partial occlusion. Besides that, the color of the vehicle is easier to be detected and the processing time to obtain the color information is much faster than other parameters. The information of the target model can be obtained by generating the color histogram. The histogram is normally calculated in the RGB color space using 8 x 8 x 8 bins would be a discrete histogram. After obtaining the color histogram of the sample, it will be comparing with the color histogram of the reference in order to calculate the similarity of the two histograms. A popular method that used for measuring the similarity of two distributions is Bhattacharyya coefficient. Bhattacharyya coefficient is used to determine the likelihood and calculate the weighting of the respective particle samples in this study.

IV. BHATTACHARYYA COEFFICIENT

Bhattacharyya coefficient is a popular measurement between two color distributions [8]. It defines a normalized distance among color histogram of references, $p(u)$ and color histogram of samples, $q(u)$ as in (3).

$$\rho[p,q] = \int \sqrt{p_u q_u}\, du \quad (3)$$

Since, the color histogram is a discrete density. Therefore, the coefficient is defined as in (4),

$$\rho[p,q] = \sum_{u=1}^{N_c} \sqrt{p_u q_u} \quad (4)$$

where $p = \{p_u\}_{u=1...N_c}$ and $q = \{q_u\}_{u=1...N_c}$.

The larger the coefficient ρ represents the more similarities of the color distributions between the reference and target color distribution. For two identical normalized color histograms, the Bhattacharyya coefficient, $\rho = 1$.

V. TARGET LOCALIZATION

After weighing the entire particle by the likelihood, the weak particle or the low weight particle will be eliminated and resample a new set of sample to replace those unwanted particle to avoid the particle degeneracy problem occur. After resampling, the particle will be distributed more concentrate and focus to the center of the target. Hence, in this particle filter algorithm, the location of the vehicle can be easily localized through the mean coordinates generated by the particles of the target in the area of interest.

VI. RESAMPLING ALGORITHM

A. *Particle Degeneracy*

Particle filter is a powerful and proven algorithm that used for object tracking for non-Gaussian and non-linear distribution. It consists of three basic stages which are initialization, prediction, and updating to form a single iteration of the recursive algorithm. However, after a few iterations, the particle degeneracy will occur and cannot be avoided. Therefore resampling is needed to overcome the degeneracy problem.

In order to measure the particle degeneracy, calculation of the effective sample size N_{eff} is shown in (5).

$$N_{eff} = \frac{N_s}{1 + Var(w_t^{*i})} \quad (5)$$

where $w_t^{*i} = \dfrac{p(x_t^i \mid z_{1:t})}{q(x_t^i \mid x_{t-1}^i, z_t)}$ is referred to the true weight. In this case, the true weight cannot be evaluated, and hence an estimation of N_{eff} need to be generated as in (6),

$$\hat{N}_{eff} = \frac{1}{\sum_{i=1}^{N_s} (w_t^i)^2} \tag{6}$$

where w_t^i is the normalized weight as in (2). Therefore, based on (5), it can be noticed that $N_{eff} \le N_s$ indicates particle degeneracy will occur. Although a very large sample size might improve the accuracy of the particle filter tracking, its computational cost will be very expensive. Therefore, the most efficient and common way to solve this degeneracy phenomenon is to adapt the resampling process.

B. Traditional Resampling

Resampling is one of the ways to solve the particle degeneracy problem. Therefore, many researchers have done research on different resampling algorithm. For example, multinomial resampling, residue resampling, systematic resampling and stratified resampling are among the most common resampling algorithm that used to reduce the particle degeneracy problem. Table I shows the traditional resampling algorithm that normally used to reduce the degeneracy problem.

TABLE I. TRADITIONAL RESAMPLING ALGORITHM

Traditional Resampling Algorithm

$[\{x_t^{*i}, w_t^i\}_{i=1}^N] = RESAMPLE[\{x_t^i, w_t^i\}_{i=1}^N]$

Calculate the $\hat{N}_{eff}$, $\hat{N}_{eff} = \dfrac{1}{\sum_{i=1}^{N_s} (w_t^i)^2}$

IF $\hat{N}_{eff} < T_{thres}$

  Resample the discrete distribution

  $\{w_t^i : i = 1,\ldots, N\}$

  Generate new set of particles

  $\{\hat{x}_t^i : i = 1,\ldots, N\}$

  Weighting the particles

  $\{\hat{x}_t^i = x_t^i = w_t^i\}$

ELSE

  $\{\hat{x}_t^i = x_t^i, i = 1,\ldots, N\}$

END IF

In Table I, $\hat{N}_{eff}$ is the estimation of effective sample size which is used to determine the degeneracy of the particle weight. When degeneracy occurred during the tracking process, resampling stage will be activated to regenerate a new set of samples and weighting the new set of particle again using the color likelihood technique. If the new set of the particle is not acceptable, resampling stage is continually evaluated until the estimation of effective sample size has passed the threshold value. Therefore, the resampling process might consume heavy computational time.

Besides that, when the vehicle is being occluded, the information of the vehicle will be lost. Therefore, more iteration of resampling algorithm needs to be executed in order to get a more accurate result. More time is required to resample due to the dissimilarity color histogram of the reference with the color histogram of the target.

C. Improved Resampling

An improved particle filter approach with the adaptive function of resampling process is examined in this study. It is believed that with the adaptive function to the various occluded conditions, resampling processing time will be optimized in object tracking. In this study, only the weakest and lowest weight particles will be eliminated and

TABLE II. IMPROVED RESAMPLING ALGORITHM

Improved Resampling Algorithm

$[\{x_t^{*i}, w_t^i\}_{i=1}^N] = RESAMPLE[\{x_t^i, w_t^i\}_{i=1}^N]$

Calculate the $\hat{N}_{eff}$, $\hat{N}_{eff} = \dfrac{1}{\sum_{i=1}^{N_s} (w_t^i)^2}$

IF $\hat{N}_{eff} < T_{thres}$

  Choose the highest weight of the particle

  IF $w_t^i < w_{thres}$

    Eliminate the weak particle

    $M = M + 1$

  ELSE

    Generate remaining of particles

    $\{\hat{x}_t^i : i = 1,\ldots, N - M\}$

    Weighting the particles

    $\{\hat{x}_t^i = x_t^i = w_t^i\}$

  END IF

ELSE

  $\{\hat{x}_t^i = x_t^i, i = 1,\ldots, N\}$

END IF

resampled. Meanwhile, the particle with the accepted weight will be storing for tracking purpose. The purpose of this is to faster the resampling process. In this case, it is more suitable to be used when the vehicle is not occluded. Moreover, the resampling stage has been shortening.

However, when the vehicle is occluded, there might be wrong information obtained by the visual tracker due to lack of resampling process. This is another challenging part in visual tracking where wrong information may cause major problem after the occlusion. Therefore, when occlusion is occur, only the largest weight of particle is reserved for resampling purpose. Table II shows the improved resampling algorithm for vehicle tracking.

VII. Result and Discussion

In this section, the result of vehicle tracking using traditional resampling (Fig. 1) will be compared to the result of vehicle tracking using an improved resampling algorithm (Fig. 2). In both cases, the particle size was initialized as 200 particles. Color histogram was selected to be used in the vehicle tracking algorithm. Various color histograms were computed in the RGB color space using 8 x 8 x 8 bins. In this paper, color was chosen as the tracking parameter because color is more easily to be identified as the vehicle identity when partial occlusion occurs. Color histogram consists of discrete data. Therefore it is faster to process the data of the color. The famous method used to calculate the likelihood of the color histogram is Bhattacharyya coefficient. The more similar of the color histogram, the Bhattacharyya coefficient will return higher value with maximum value of one.

As shown in Fig. 1 and Fig. 2, the crossing icon was represented the particle distribution. Meanwhile the solid box was indicated the location of the target vehicle. The target localization was determined by the mean value of the estimated position of the particle. The mean value was selected as the coordination of target because the particle has been normalized.

Base on the results shown in Fig. 1 and Fig. 2, the tracking was divided into four cases, namely the vehicle before occluded, partially occluded, fully occluded and after occluded. Referred to the sequence of results shown in Fig. 1 and Fig. 2, the adaptive particles filter resampling shown the much more promising result. The target vehicle was successfully being tracked throughout the video although it was fully occluded at Frame 32.

In case 1, the moving vehicle occurred before the occlusion as shown in Frame 26 of Fig. 1 and Fig. 2. The traditional and improved particle filter resampling algorithm was able to track the moving vehicle. In this case, the particle was resampled as usual by eliminated the weak and low weight particles and resampled the particle to replace those eliminated particle.

In case 2, the moving vehicle was partially occluded as shown in Frame 29 of Fig. 1 and Fig. 2. In this case, it showed that color is a useful parameter that could be used

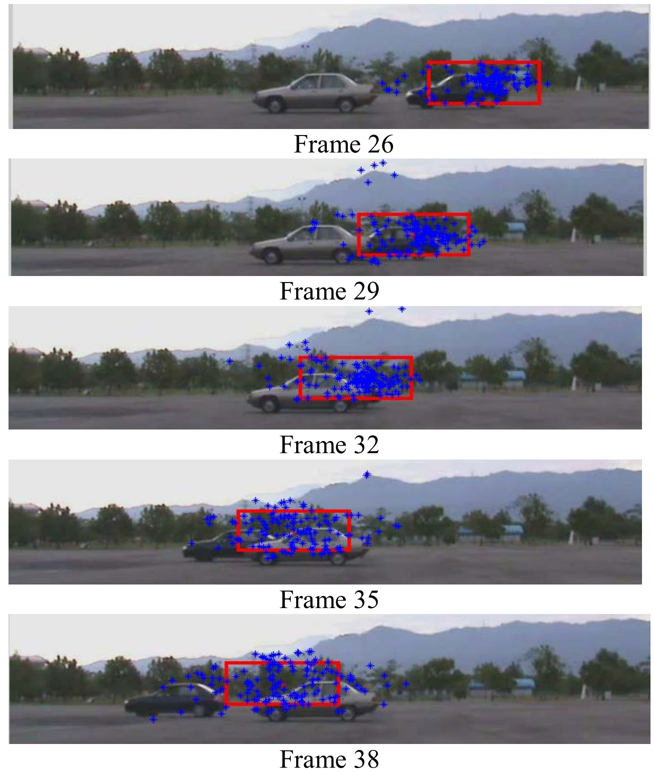

Figure 1. Result of vehicle tracking by using traditional resampling particle filter.

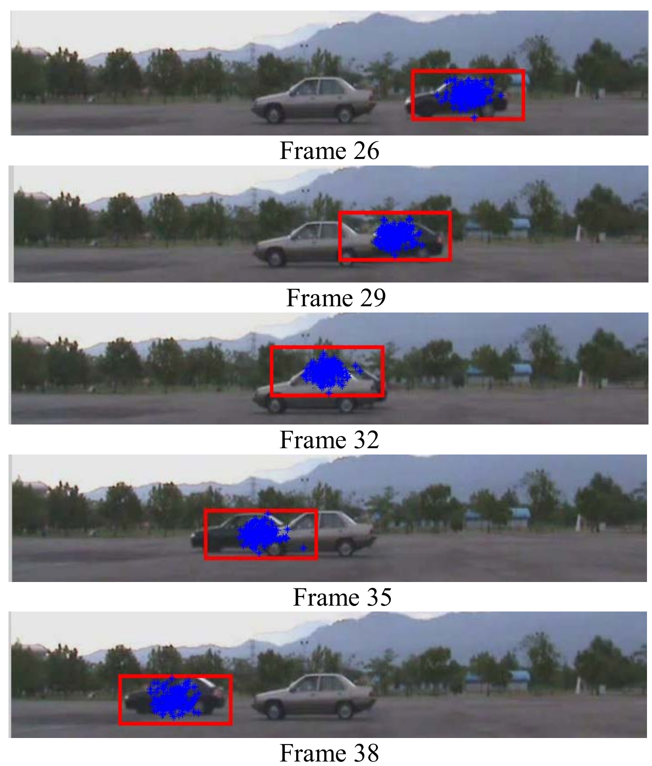

Figure 2. Result of vehicle tracking by using adaptive particle filter resampling algorithm.

for partially occlusion. When there was a different color between the two objects, color was the promising parameter for vehicle tracking purpose. In this case, the resampling algorithm still acts as usual as information of the vehicle still obtainable. Therefore, the both the algorithms were able to track the vehicle.

In case 3, the moving vehicle was almost fully occluded by another vehicle as shown in Frame 32 of Fig. 1 and Fig. 2. Majority of the information of the moving vehicle was lost. The traditional resampling algorithm failed to allocate the moving occluded vehicle with a group of heavy particles which was trapped at another vehicle. Meanwhile, the adaptive resampling algorithm selected the specific location with most similar color to the moving vehicle and resampling within that area. Therefore, the adaptive resampling was able to track the moving vehicle although a small portion of the moving vehicle color was identified.

In case 4, the moving vehicle occurred after being occluded as shown in Frame 35 of Fig. 1, the result showed that the traditional resampling algorithm was unable to track the labeled moving vehicle. The traditional resampling method failed to track the vehicle because when the moving vehicle was occluded, the information of the vehicle was lost and replaced by the color histogram of other vehicle. Therefore, the moving vehicle lost track by the visual tracker as shown in Frame 38 of Fig. 1. On the other hand, the adaptable particle resampling algorithm was able to keep track the labeled moving vehicle as shown in Frame 35 of Fig. 2. After occlusion occurs, the likelihood of the target vehicle decreased as compared to the reference histogram. The improved particle filter eliminated the entire particles except the particles with the highest weight. Based on the location of the remaining highest weighted particles, a new set of sample will be resampled. Therefore, the moving vehicle was able to be tracked by the visual tracker as shown in Frame 38 of Fig. 2.

VIII. CONCLUSION

In this paper, an adaptive resampling particle filter algorithm has been proposed for vehicle tracking purpose. As discussed in the previous section, particle degeneracy diminishes the accuracy of the tracking algorithm. In order to sufficiently avoid the particle degeneracy, resampling is an important solution to improve the performance of the tracking system. Although more particles are included into the tracking system may increase the tracking accuracy, but the computation cost will be increased heavily.

With the adaptable particle filter resampling algorithm, its capability of dealing with various occlusion incidents was shown in the results. The experimental results showed that enhancement of the particle filter via resampling algorithm had been robustly tracking the vehicles, and significantly improved the accuracy in tracking the occluded vehicles without compromising the computational time.

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