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Symmetry-Aided Particle Filter for Vehicle Tracking

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***Abstract*— Symmetry is an important characteristic of vehicle and has been used for detection tasks by many researchers. However, existing results of vehicle tracking seldom used this feature. In this paper, we combine the color histogram and the symmetry measurements to design a hierarchical-like particle filter for vehicle tracking. Experimental results show that the use of symmetry information will obtain better tracking performance than the conventional color histogram-based particle filters and effectively avoid some "hijack" problems.**

I. INTRODUCTION

As a class of important mobile robots, the intelligent vehicles have been received more and more interests since they can be used to reduce the number of traffic accidents and increase the driver comfort. Among the many functionalities an intelligent vehicle must perform, vehicle detection and tracking play important roles[3][16]. In fact, the intelligent vehicle must be able to detect and track preceding vehicles on its path in order to perform autonomous driving. Different classes of sensors, such as camera, radar, and acoustic, have been considered for sensing in this application. Due to the increasingly powerful computers and the less-expensive high-performance video cameras that have become available in the past few years, the use of computer vision technology as a sensor in driver-assistance systems become more common and has led to increased performance. Vision sensors can provide rich information about the vehicle's surroundings and also have the advantage over active sensors of not causing intervenience interference[18][2].

II. RELATED WORKS

The search for vehicle features provides a simplified way of localizing vehicles. Among the features, symmetry is a characteristic that is common to most vehicles[16]. Some researchers have already used symmetry to detect vehicles [3] [4][8][20]. They have proposed varied approaches to find symmetry on images: using edges, pixel intensity, and other features. Especially, [20] pointed out that the mirror symmetry with respect to a vertical axis is ont of the most striking generic shape features available for object recognition in a vehicle-following situation. The obtained vertical axis of symmetry is an excellent feature for measuring the leading vehicle's relative lateral displacement in consecutive images because it is invariant under vertical nodding movements of the camera and under changes of object size. However, though the symmetry property is a strong feature of vehicles, it is up to now mainly used in the field of vehicle detection. For vehicle tracking, only [1] and [15] recently tried to used the symmetry features, but their results were based on the combination information of vision and radar.

As to the tracking algorithm, earlier results were based on the famous Kalman filtering[5], which can obtain optimal solution in the case of linear dynamics and Gaussian noise. Unfortunately, very few practical visual tracking problems belong to this case. For nonlinear or non-Gaussian problems, it is impossible to evaluate the probability distribution analytically and many algorithms have been proposed to approximate them. The particle filter, also known as sequential Monte Carlo[6], or Condensation[9], is the most popular approach which recursively constructs the posterior probability distribution function of the state space using Monte Carlo integration. Currently, the particle filter has been extensively used in the field of environment sensing, navigation, and SLAM for robots[7][13][14].

The particle filter based tracking algorithms usually uses contours[9], color features[12], or appearance models [19]. The color histogram is robust against noise and particle occlusion, but suffers from the presence of the confusing colors in the background. In [18], the color histogram and the edge-gradient-based shape features are combined to track vehicles. In [19], only the gray-scale appearance model is used. These approaches are difficult to deal with the "hijack" problem in multiple-object tracking, which will be illustrated in the following section. Recently, [15] and [1] incorporated the symmetry information into the particle filter framework to track vehicles, which show excellent performance with the aid of radar information.

In this paper, we will use the color histogram and the symmetry measurements to design a hierarchical-like particle filter for vehicle tracking. Experimental results show that the use of symmetry information will strongly increase the tracking performance than the conventional color histogram-based particle filters. In addition, the calculation of symmetry and the combination way of different features are very different from the algorithms in [15] and [1]. More importantly, only visual information is needed in this paper, while [15] and [1] used both visual and radar information.

III. BRIEF REVIEW FOR PARTICLE FILTER

The task of tracking is to use the available measurement information to estimate the hidden state variables. Given the available observations $\mathbf{z}_{1:k-1} = \mathbf{z}_1, \mathbf{z}_2, \cdots, \mathbf{z}_{k-1}$ up to time instant $k-1$, the prediction stage utilizes the probabilistic system transition model $p(\mathbf{x}_k|\mathbf{x}_{k-1})$ to predict the posterior

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at time instant k as

$$p(\mathbf{x}_k|\mathbf{z}_{1:k-1}) = \int p(\mathbf{x}_k|\mathbf{x}_{k-1})p(\mathbf{x}_{k-1}|\mathbf{z}_{1:k-1})d\mathbf{x}_{k-1} \quad (1)$$

At time instant k, the observation $\mathbf{z}_k$ is available, the state can be updated using *Bayes's* rule

$$p(\mathbf{x}_k|\mathbf{z}_{1:k}) = \frac{p(\mathbf{z}_k|\mathbf{x}_k)p(\mathbf{x}_k|\mathbf{z}_{1:k-1})}{p(\mathbf{z}_k|\mathbf{z}_{1:k-1})} \quad (2)$$

where $p(\mathbf{z}_k|\mathbf{x}_k)$ is described by the observation equation.

In general, the integrals in (1) and (2) are analytically intractable. To solve this problem, the particle filter approaches are proposed [6]. The kernel of particle filter is to recursively approximate the posterior distribution using a finite set of weighted samples. Each sample $\mathbf{x}_k^i$ represents one hypothetical state of the object, with a corresponding discrete sampling probability ω_k^i, which satisfies $\sum_{i=1}^N \omega_k^i = 1$. The posterior $p(\mathbf{x}_k|\mathbf{z}_{1:k})$ then can be approximated as $p(\mathbf{x}_k|\mathbf{z}_{1:k}) \approx \sum_{i=1}^N \omega_k^i \delta(\mathbf{x}_k - \mathbf{x}_k^i)$, where $\delta(\cdot)$ is Dirac function. Then the estimation of the state $\mathbf{x}_k$ can be obtained as $\hat{\mathbf{x}}_k = E_p[\mathbf{x}_k|\mathbf{z}_{1:k}] \approx \sum_{i=1}^N \omega_k^i \mathbf{x}_k^i$. The candidate samples $\{\mathbf{x}_k^i\}_{i=1,2,\cdots,N}$ are drawn from an importance distribution $q(\mathbf{x}_k|\mathbf{x}_{1:k-1},\mathbf{z}_{1:k})$ and the weight of the samples are

$$\omega_k^i = \omega_{k-1}^i \frac{p(\mathbf{z}_k|\mathbf{x}_k^i)p(\mathbf{x}_k^i|\mathbf{x}_{k-1}^i)}{q(\mathbf{x}_k|\mathbf{x}_{1:k-1},\mathbf{z}_{1:k})} \quad (3)$$

The samples are re-sampled to generated an unweighed particle set according to their importance weights to avoid degeneracy. In the case of the bootstrap filter[6], $q(\mathbf{x}_k|\mathbf{x}_{1:k-1},\mathbf{z}_{1:k}) = p(\mathbf{x}_k|\mathbf{x}_{k-1})$ and the weights become the observation likelihood $p(\mathbf{z}_k|\mathbf{x}_k)$.

IV. Observation models

A. Color histogram

First, we will recall the particle filter in a color-based context[12][11][18]. Color distributions are used as object models as they achieve robustness against non-rigidity, rotation and partial occlusion. In our experiments, the histograms are typically calculated in the RGB space using $8 \times 8 \times 8$ bins. The resulting complete histogram is thus composed of $N_h = 512$ bins.

The color-similarity measure is based on the similarity between the color histogram of a reference region and that of the image region in frame k represented by a sample $\mathbf{x}_k^i$. To estimate the proper weight for this sample during the measurement update step, we need the observation model $p(\mathbf{z}_k|\mathbf{x}_k = \mathbf{x}_k^i)$. This model can be obtained by the following equation

$$p(\mathbf{z}_k|\mathbf{x}_k = \mathbf{x}_k^i) \propto \exp\{-\lambda D^2(\mathbf{q}^*, \mathbf{q}_k(\mathbf{x}_k^i))\} \quad (4)$$

where λ is an experimentally determined constant and $\mathbf{q}^*$ and $\mathbf{q}_k(\mathbf{x}_k^i)$ are the color histograms of the reference region and the region defined by $\mathbf{x}_k^i$, respectively. The distance measure $D(\cdot,\cdot)$ is derived from the Bhattacharyya similarity coefficient and is defined as

$$D(\mathbf{q}^*, \mathbf{q}_k(\mathbf{x}_k^i)) = \{1 - \sum_{n=1}^{N_h} \sqrt{q^*(n)q_k(n;\mathbf{x}_k^i)}\}^{1/2} \quad (5)$$

More details can be found in [12] and [11]. Although color histogram is a robust feature, it also present some disadvantages. For example, when dealing with multiple objects with similar color histograms, using the color histogram feature only is not enough since when the objects pass close to one another, the object with the best likelihood score will "hijack" the filters of nearby objects[10]. This is illustrated in Fig.7. In this case, two independent particle filters using color histogram features are used to track two independent vehicles. In Frame 310, the filters works well. However, in the next two frames (Frames 311-312), the vehicle (in *yellow*) with better likelihood score "hijack" the filters of nearby vehicle (in *red*). Finally, the tracking for the left vehicle will completely fail from Frame 313. From the following sections we can see that incorporating symmetry information into this framework will improve the results.

Fig. 1. LEFT: Frame 310; RIGHT: Frame 311

Fig. 2. LEFT: Frame 312; RIGHT: Frame 313

Fig. 3. LEFT: Frame 314; RIGHT: Frame 315

B. Symmetry

Since in this application each sample is a rectangle box, which represents a candidate vehicle, we can compute its strength of symmetry. Intuitively, if a sample rectangle box shows strong symmetry, it will be more possible be a vehicle. For computing the symmetry, the intensity distribution of each row of the sample rectangle can be regarded as a one-dimensional function. Assume the center location of i-th sample rectangle is $(x_s^{(i)}, y_s^{(i)})$, and the width is $w^{(i)}$. For the given $w^{(i)}$ and $x_s^{(i)}$, we can compute the following two functions:

$$E_l^{(i)}(u)=\begin{cases}\frac{G(l,x_s^{(i)}+u)+G(l,x_s^{(i)}-u)}{2} & \text{if } -w^{(i)}/2\le u\le w^{(i)}/2\\ 0 & \text{otherwise}\end{cases} \tag{6}$$

$$O_l^{(i)}(u)=\begin{cases}\frac{G(l,x_s^{(i)}+u)-G(l,x_s^{(i)}-u)}{2} & \text{if } -w^{(i)}/2\le u\le w^{(i)}/2\\ 0 & \text{otherwise}\end{cases} \tag{7}$$

where $G(\cdot,\cdot)$ is the corresponding gray scale image of current frame. It is obvious that $E_l^{(i)}(u)$ is an even function and $O_l^{(i)}(u)$ is an odd function. For fair comparison purpose, the function $E_l^{(i)}(u)$ should be normalized as

$$\hat{E}_l^{(i)}(u)=E_l^{(i)}(u)-\frac{2}{w^{(i)}}\int_0^{w^{(i)}/2}E_l^{(i)}(v)dv \tag{8}$$

Since both $O_l^{(i)}(u)$ and $\hat{E}_l^{(i)}(u)$ are odd functions, we can define

$$S_l^{(i)}=\frac{\int_0^{w^{(i)}/2}|\hat{E}_l^{(i)}(u)|du-\int_0^{w^{(i)}/2}|O_l^{(i)}(u)|du}{\int_0^{w^{(i)}/2}|\hat{E}_l^{(i)}(u)|du+\int_0^{w^{(i)}/2}|O_l^{(i)}(u)|du} \tag{9}$$

In general, the value $S_l^{(i)}$ will locate in the interval $[-1,1]$. $S_l^{(i)}=1$ represents ideal symmetry and $S_l^{(i)}=-1$ represents ideal antisymmetry. Therefore we can use this value to measure the symmetry property of the i-th sample rectangle. Assume the i-th sample box has $H^{(i)}$ rows, then we have to compute this value row by row and the whole symmetry measurements for this sample box is

$$\bar{S}^{(i)}=\frac{1}{H^{(i)}}\sum_{l=1}^{H^{(i)}}S_l^{(i)} \tag{10}$$

Remark 4.1: Different from existing results, such as [20], the symmetry function in (9) are defined by using the absolute value rather than square operator. This will reduce computation time and shows better performance in our practice.

V. PROPOSED PARTICLE FILTER

In the above section we give a symmetry measurement approach for the sample boxes. A natural idea is to incorporate this measurement into the weights of the color histogram and form a combined weight. Since both color histogram and symmetry can be used to design the particle filter, the performance will be expected to be better, especially for cases where the color histogram features fail to distinguish the objects. On the other hand, though Eq.(10) can be used to measure the symmetry strength of a sample box, it is not precise due to the clutter, noise, and so no, and therefore the obtained value is of just qualitative sense. In this work, we propose a hard decision to combine them, the main procedure is illustrated as follows.

After we obtain the predicted samples by using the prior dynamics, we first compute the symmetry strength for each sample. It is obvious that boxes with stronger symmetry will more be possible be the object (vehicle). On the contrary, if a sample box have very weak symmetry strength, it will not be considered for further sampling. Therefore we can used the following hard decision: If the symmetry strength of one box is smaller than a prescribed threshold, then we will delete it from the sample set. More concisely, we directly set its weight to be zero. Otherwise, the weight of the sample is determined by the color histogram. From these steps we can see that we do not use the precise value of the symmetry strength when computing the weights. It should be noted that at some step, if none of the sample boxes has symmetry strength which is larger than the threshold, then we will set all of the weights to be zeros. This is not expected since the sample set will be empty. To avoid this, we can adjust the threshold to some extent. In our experiments, we set the threshold to be zero, which shows excellent performance in our experiments.

Algorithm 1 `Proposed Particle Filter`

Initialize the reference color histogram $\mathbf{q}^*=\{q^*(n)\}_{n=1,2,\cdots,N_h}$, a sample set $S_0=\{\mathbf{x}_0^i,1/N\}_{i=1,\cdots,N}$
Prediction: For $i=1,2,\cdots,N$, draw predicted particles $\hat{\mathbf{x}}_{k+1}^i$ from the prior dynamics $p(\mathbf{x}_{k+1}|\mathbf{x}_k)$: $\hat{\mathbf{x}}_{k+1}^i\sim p(\mathbf{x}_{k+1}|\mathbf{x}_k=\mathbf{x}_k^i)$
Symmetry computation: For $i=1,2,\cdots,N$, compute the symmetry strength $\bar{S}^{(i)}$ of each sample box $\hat{\mathbf{x}}_{k+1}^i$ according to (10)
Determine the weights:For every $i=1,2,\cdots,N$,
IF $\bar{S}^i>th$, then compute the color histogram $\mathbf{q}_{k+1}(\hat{\mathbf{x}}_{k+1}^i)$, and determine the weight value $\hat{\omega}_{k+1}^i$ according to (4).
ELSE set the weight value $\hat{\omega}_{k+1}^i=0$.
Normalize the weights: $\omega_{k+1}^i=(\sum_{i=1}^N\hat{\omega}_{k+1}^i)^{-1}\hat{\omega}_{k+1}^i$
Re-sampling:For $i=1,2,\cdots,N$, sample index i' from discrete probability $\{\omega_{k+1}^i\}$ over $\{1,2,\cdots,N\}$, and set $\mathbf{x}_{k+1}^i=\hat{\mathbf{x}}_{k+1}^{i'}$.

Remark 5.1: In previous works, there exist several conventional combination approach. Concretely speaking, if we have two weights ω_1 and ω_2. Two representative combinations are $\omega=\alpha\omega_1+(1-\alpha)\omega_2$[18], and $\omega=\omega_1\omega_2$, respectively. These combinations are intuitive but do not use the more intrinsic properties.

Remark 5.2: The re-sampling step, which is important in particle filter, can efficiently avoid the sample degeneracy problem [6].

VI. EXPERIMENTAL RESULTS

In this section, the proposed particle filter is used to track vehicles in the road. We have done a lot of experiments, including single and multiple object tracking.For all of the experiments, the state of the particle filter is defined as $\mathbf{x}_k=[x_k,y_k,s_k]$, where x_k,y_k indicate the location of the object, s_k the scale. The dynamics of the objects are assumed to be a random walking model, which can be represented as $\mathbf{x}_k=\mathbf{x}_{k-1}+\mathbf{v}_k$, where $\mathbf{v}_k$ is a multivariate zero-mean Gaussian random variable. Its variances are set by $[\sigma_x,\sigma_y,\sigma_s]=[10,10,0.1]$. For each particle filter, we assign 200 samples.

We can initialize the particle filter and the reference color histogram with a detector algorithm (such as Adaboost approach[17]) or a manfully specified image patch in the first frame. The image sizes of all of the sequence are 640×480. For fair comparison, all of the particle filters for one sequence are started with same initial detection results.

A. Single vehicle tracking

We first consider a simple case: Single vehicle tracking. See Figs.4-7 for some representative results, where Fig.4 and Fig.6 show the tracking results using our algorithm, Fig.5 and Fig.7 shows the results of a particle filtering which use color-histogram cue only.

In this example, we can see there are only small changes in the locations and scale for the actual vehicle motion throughout the whole sequence. However, even in this case, the color-histogram based approach often gives results with deflection. Our approach, since use the symmetry information, can obtain more accurate location estimation.

Fig. 4. Proposed approach: Frames 5, 15, 25, 35

Fig. 5. Color histogram-based approach: Frames 5, 15, 25, 35

Fig. 6. Proposed approach: Frames 40, 50, 60 ,80

Fig. 7. Color histogram-based approach: Frames 40, 50, 60, 80

B. Multiple vehicle tracking

In the first experiment, we consider the example which is introduced in Section VI.A. We also use two independent particle filters, which implement the proposed algorithms, to track the two vehicles. The tracking results corresponding to Frames 310-315 are shown in Figs.8-10. By comparison of Figs.1-3, we can see that the “hijack” problem is efficiently avoided even in the case when the two vehicles are very near. The reason is that though the right vehicle, which can obtain high likelihood score, attempts “hijack” the particle filter of the left vehicle, the symmetry constraint make the weights of these wrong samples very low, and these wrong samples will be eliminated by our algorithm.

Fig. 8. LEFT: Frame 310; RIGHT: Frame 311

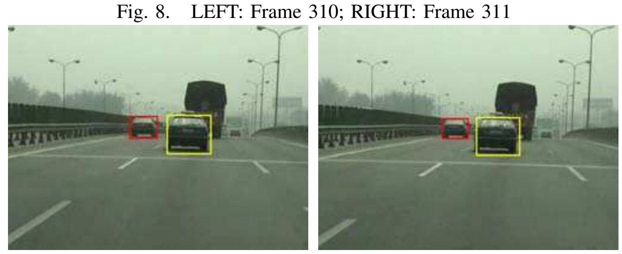

Fig. 9. LEFT: Frame 312; RIGHT: Frame 313

Fig. 10. LEFT: Frame 314; RIGHT: Frame 315

Next, we consider a more complicated case: multiple vehicle tracking with partial occlusion. When one vehicle is occluded by others, it is obvious that the symmetry property will lost. In this case, we can de-active the symmetry calculation module and recover the proposed algorithm to conventional color-histogram-based algorithm. That is to say, only color histogram cue is used during the occlusion period. Then, another problem arise: How to detect the occlusion? To completely solve this problem is difficult and it beyonds the scope of this paper. In this paper, we use a simple but efficient decision function to judge whether occlusion happen or not. For simplicity, we consider two vehicles only.

At each step of the tracking, we first use the detected results obtained in the last step to judge the occlusion. Assume that the detection results of last instant are $[x_{k-1}(1), y_{k-1}(1), s_{k-1}(1)]$ and $[x_{k-1}(2), y_{k-1}(2), s_{k-1}(2)]$. From these state variables we can obtain the corresponding bounding boxes $BOX(1)$ and $BOX(2)$, which are rectangles. Then, if the two boxes are overlapped, we can declare occlusion and cancel the symmetry computation; Otherwise, we declare no occlusion and use the symmetry-aided approach to track the vehicles. This mechanism is simple but it is efficient in our practice.

Figs.11-20 give some representative tracking results. Here we compare three approach: Approach 1 uses color histogram feature only; Approach 2 and Approach 3 use both color histogram and symmetry features. The difference between Approach 2 and Approach 3 is that there is no occlusion handling in Approach 2.

Fig. 11. Approach 1: Frame 20, 25, 30, 35

Fig. 12. Approach 2: Frame 20, 25, 30, 35

Fig. 13. Approach 3: Frame 20, 25, 30, 35

Fig. 14. Approach 1: Frame 70, 80, 90, 100

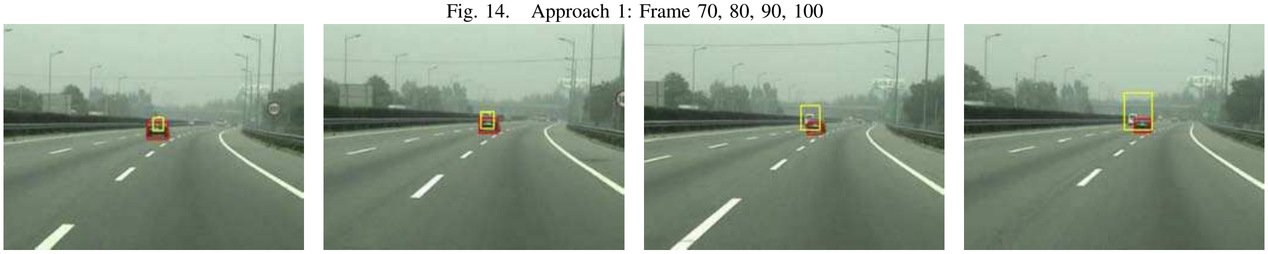

Fig. 15. Approach 2: Frame 70, 80, 90, 100

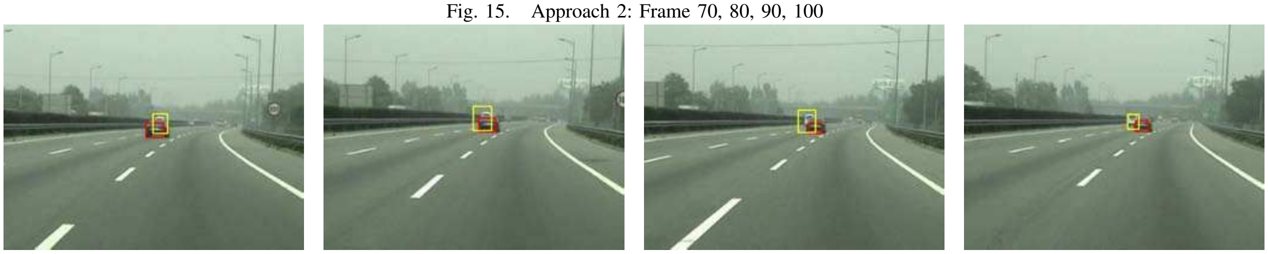

Fig. 16. Approach 3: Frame 70, 80, 90, 100

From Figs.11-13 we can see that even when the two vehicles are not near, the proposed approaches (Approach 2 and Approach 3) perform better than Approach 1. Figs.14-16 show representative frames corresponding to occlusion case.

During the occlusion period, using Approach 3 can track the two vehicles accurately, while the results using Approach 1 are rather poor, especially for the occluded vehicle(see Fig.14, *yellow* boxes). In addition, since there is no occlusion handling in Approach 2, the tracking algorithm will still use the symmetry feature, which is not reliable when the vehicle is occluded. The tracking results in Fig.15 show that the algorithm can track two vehicles when the occlusion just happens, but the tracking result for the occluded vehicle will rapidly deteriorate (see Fig.15, Frame 90, Frame 100). We further give some more tracking results for frames after occlusion in Figs.17-20. It shows that Approach 2 will fail after occlusion, while Approach 3 can still give satisfactory results.

Fig. 17. Frame 110. LEFT: Approach 2; RIGHT: Approach 3

Fig. 18. Frame 120. LEFT: Approach 2; RIGHT: Approach 3

Fig. 19. Frame 130. LEFT: Approach 2; RIGHT: Approach 3

Fig. 20. Frame 140. LEFT: Approach 2; RIGHT: Approach 3

VII. Conclusions

Symmetry is an important property for vehicle. In this paper, this feature is used to improve the vehicle tracking. A hierarchical-like particle filter which incorporates the symmetry measurement and color histogram is designed for vehicle tracking, which can effectively improve the tracking performance and efficiently avoid the “hijack” problem which is often encountered by the conventional color-histogram-based particle filter.

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