ROBUST MULTI-TARGET TRACKING USING MEAN SHIFT AND PARTICLE FILTER WITH TARGET MODEL UPDATE

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Abstract: We propose a novel multiple targets tracking algorithm combining Mean Shift and Particle Filter, and enhance the performance with target model update process. Mean Shift has a low complexity, but is weak in dealing with multi-modal probability density functions (*pdf*s). Particle Filter is robust to the partial occlusion and can deal with multi-modal *pdf*s. In real application, illumination conditions, the visual angle as well as object occlusion can change target appearance, thus influence the quality of Particle Filter. For multi-target tracking task, the mutual occlusion of targets and computational complexity are important problems for tracking system. In this paper, Mean Shift algorithm is embedded into Particle Filter framework to get stable tracking and reduce computational load. To overcome the target appearance changes caused by illumination changes and object occlusion, targets model are updated adaptively during tracking. Experimental results show that our tracking system can robustly track multiple targets with mutual occlusion and correctly maintain their identities with smaller number of particles than Particle Filter.

1 INTRODUCTION

Tracking multiple targets has been of broad interest in many computer vision applications for decades. A visual based multi-target tracking system should be able to track multiple objects in a dynamic scene and maintain the correct identities of the targets regardless of occlusions and any other visual perturbations (Cai, Nando, 2006). We address the problem of robust and fast multi-target tracking.

Tracking algorithms can be classified into two major groups. The first group is Target Representation and Localization algorithm, the second group is Filtering and Data Association algorithm (Comaniciu, Ramesh, 2003). The Mean Shift (MS) algorithm (Comaniciu, Ramesh, 2003) is a non-parametric method which belongs to the first group. MS is an iterative kernel-based deterministic procedure which converges to a local maximum of the measurement function under certain assumptions on the kernel behaviors. On the one hand, MS is the algorithm with low complexity, which provides a general and reliable solution independently from the features representing the target. On the other hand, MS fails in tracking small and fast moving targets (Comaniciu, Ramesh, 2003). Particle Filter (PF) is a parametric method which belongs to the second group. PF solves non-linear and non-Gaussian state estimation problems (Arulampalam, Maskell, 2002) and can deal with multi-modal *pdf*s. The number of particles needed to model the variations of the underlying *pdf* increases exponentially with the dimensionality of the state space, thus increasing the computational load (Maggio, Cavallaro, 2005).

For multi-target tracking task, with the increasing of targets number, the particles also increased dramatically to maintain correct tracking, which will also bring computational complexity problem (Cai, Nando, 2006). In real applications, illumination conditions, the visual angle as well as the mutual occlusion of targets will change the appearance of targets, thus influence the performance of Particle Filter (Nummiaro, Koller, 2002). A hybrid PF and MS tracking algorithm TSHT was used to reduce particle number compared with Particle Filter (Maggio, Cavallaro, 2005). But in their experiment, TSHT was applied for tracking single target with no occlusion and appearance change. In literature (Cai, Nando, 2006), Mean Shift was also embedded into Particle Filter framework to stabilize the trajectories of targets for multi-target tracking. But they assigned much more particles in the first stage and haven't analyzed the influence of computational complexity after embedding Mean Shift into Particle Filter. The above methods have not taken the

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updating of the target model into consideration, which is actually important in real applications. Literature (Shan, Wei, 2004) used target model update process, but is applied for tracking single target.

This paper proposes a novel method for multiple targets tracking. Particle Filter framework is adopted which uses Monte Carlo sampling method to resolve non-Gaussian and non-linear state estimation problem of video tracking. In initial stage, an independent particle filter tracker is assigned for each target. Target model uses the weighted color histogram, which is robust to illumination changes and partly occlusion. Targets model are updated adaptively during tracking to fit the changes of target appearance. To reduce computing complexity of multi-target tracking, we embedded Mean Shift into particle filter framework after importance sampling process. After Mean Shift aggregates, particles are closer to the local maximum corresponding to the true position of targets. Thus, in initialization stage, only a fewer number of particles can maintain the correct tracking. We name our method as MSPFU (Mean Shift embedded Particle Filter with target model Update).

The paper is organized as follows. Section 2 introduces the target model, existing tracking algorithms. The proposed tracking system MSPFU is discussed in Section 3. Experimental results are presented in Section 4. Finally, in Section 5 we draw the conclusions.

2 CONVENTIONAL METHOD

2.1 Target Model

We adopt the weighted color histogram as target model (Comaniciu, Ramesh, 2003) in our application. The color histogram is a widely used form of target representation for it is successful in tracking non-rigid objects with partial occlusion and rotation. The model is originally introduced by Comaniciu et al. (Comaniciu, Ramesh, 2003) for the mean-shift based object tracking.

We define the target as its normalized color histogram, $q = \{q_u\}_{u=1,\dots,m}$, where m is the number of bins. The normalized color distribution of a initial target model $q(y)$ centered in y can be calculated as

$$q_u(y) = C_h \sum_{i=1}^{n_h} k\left(\left\|\frac{y-x_i}{h}\right\|^2\right)\delta\left[b(x_i)-u\right] \tag{1}$$

where $\{x_i\}_{i=1,\dots,n_h}$ are the n_h pixel locations of the target candidate in the target area, $b(x_i)$ associates the pixel x_i to the histogram bin, $k(x)$ is the kernel profile with bandwidth h. The bandwidth h determines the scale of the target candidate. And $k(x)$ is a kernel profile of kernel K that can be written in terms of a profile function $k:[0,\infty)\to R$ such that $K(x)=k(\|x\|^2)$. According to (Comaniciu, Ramesh, 2003), the kernel profile $k(x)$ should be nonnegative, nonincreasing, piecewise continuous, and $\int_0^\infty k(r)dr < \infty$.

The term C_h in Eq.(1) is a normalization function defined as

$$C_h = \frac{1}{\sum_{i=1}^{n_h} k\left(\left\|\frac{y-x_i}{h}\right\|^2\right)} \tag{2}$$

The same equations are used to obtain the target candidate centered by y' is $p_u(y')$. In order to calculate the likelihood of a candidate a similarity function is needed which defines a distance between the model and the candidate. We use the Bhattacharryya coefficient (Comaniciu, Ramesh, 2003) to calculate similarity, defined between two normalized histograms $p(y')$ and $q(y)$ as Eq.(3). The corresponding distance is defined as Eq.(4).

$$\rho(p(y'),q(y)) = \sum_{u=1}^{m}\sqrt{p_u(y')q_u(y)} \tag{3}$$

$$d(p(y'),q(y)) = \sqrt{1-\rho(p(y'),q(y))} \tag{4}$$

2.2 Particle Filter

The Particle Filter is a Bayesian sequential importance sampling technique, which recursively approximates the posterior distribution using a finite set of weighted samples (Arulampalan, Maskell, 2002). It consists of essentially two steps: prediction and update. Given all available observations $z_{1:k-1}$ up to time k-1, the prediction stage uses the probabilistic system state transition model (Maggio, Cavallaro, 2005)

$$p(x_k \mid x_{k-1}) \tag{5}$$

to predict the posterior at time k as

$$p(x_k \mid z_{1:k-1}) = \int p(x_k \mid x_{k-1})p(x_{k-1} \mid z_{1:k-1})dx_{k-1} \tag{6}$$

At time k, the observation z_k is available, and the state can be updated using Bayes' rule

$$p(x_k \mid z_{1:k}) = \frac{p(z_k \mid x_k)p(x_k \mid z_{1:k-1})}{\int p(z_k \mid x_k)p(x_k \mid z_{1:k-1})dx_k} \tag{7}$$

where $p(z_k \mid x_k)$ is described by the observation equation. In the particle filter, the posterior $p(x_k \mid z_{1:k})$ is approximated by a finite set of N_s samples $\{x_k^i\}_{i=1,\dots,N_s}$ with importance weights ω_k^i.

$$p(x_k \mid z_{1:k}) \approx \sum_{i=1}^{N_s} \omega_k^i \delta(x_k - x_k^i) \qquad (8)$$

The candidate samples x_k^i are drawn from an importance distribution (proposal distribution) $q(x_k \mid x_{k-1}, z_{1:k})$ and the weight of the samples are

$$\omega_k^i \propto \omega_{k-1}^i \frac{p(z_k \mid x_k^i)p(x_k^i \mid x_{k-1}^i)}{q(x_k^i \mid x_{k-1}^i, z_{1:k}))}, \qquad \sum_{i=1}^{N_s} \omega_k^i = 1 \qquad (9)$$

In the case of the bootstrap filter (Arulampalan, Maskell, 2002), $q(x_k \mid x_{k-1}, z_{1:k}) = p(x_k \mid x_{k-1})$ and the weights become the observation likelihood $p(z_k \mid x_k)$ according to Eq.(9). The observation probability of each particle sample in every Particle Filter

$$\omega_k^i = \frac{1}{\sqrt{2\pi}\sigma} \exp\{-\frac{d^2(p(y), q)}{2\sigma^2}\} \qquad (10)$$

is specified by a Gaussian with variance σ. During filtering, samples with a high weight may be chosen several times, leading to identical copies, while others with relatively low weights may not be chosen at all.

The best state at the time k is derived based on the discrete approximation of Eq.(8). The most common solution is the Monte Carlo approximation of the expectation

$$E(x_k) = \sum_{i=1}^{N_s} \omega_k^i x_k^i \qquad (11)$$

Resampling of the particles is necessary from time to time in each iteration to avoid degeneracy of the importance weights. With the prediction process, PF can track fast small targets. The major limit of PF is the limited capability of the particles to describe the *pdf* when the state space is not densely sampled (Cai, Nando, 2006). To overcome this problem, a large number of particles is required thus increasing the computational load (Maggio, Cavallaro, 2005). For multiple targets tracking task, the computational complexity will increased more dramatically than for single target tracking task.

2.3 Mean Shift

Mean Shift is a nonparametric statistical method that seeks the mode of a density distribution in an iterative procedure (Comaniciu, Ramesh, 2003). The MS algorithm is an iterative process that aims at minimizing the distance in Eq.(4). The process is initialized with the location of the target in the previous frame, y_0. The shape of the kernel is chosen so that the distance becomes a smooth function (Comaniciu, Ramesh, 2003). Then, based on gradient information, the MS algorithm converges to the nearest local minimum. Looking at Eq.(3) and Eq.(4), it is possible to notice that minimizing Eq.(4) corresponds to maximizing Eq.(3). Using the Eq.(1) by computing the Taylor expansion of the Bhattacharryya coefficient around the starting position y_0, we obtain the following expression

$$\rho(p(y), q) \approx \frac{1}{2}\sum_{u=1}^{m}\sqrt{p_u(y_0)q_u} + \frac{C_h}{2}\sum_{i=1}^{n_h} w_i k\left(\left\|\frac{y - x_i}{h}\right\|^2\right) \qquad (12)$$

In the right part of Eq.(12), the first term does not depend on y. Therefore we need to maximize only the second term of Eq.(12). At each step of the iterative process, the estimated target moves from y_0 to the new location y_1, defined as

$$y_1 = \sum_{i=1}^{n_h} x_i w_i g\left(\left\|\frac{y_0 - x_i}{h}\right\|^2\right) \Bigg/ \sum_{i=1}^{n_h} w_i g\left(\left\|\frac{y_0 - x_i}{h}\right\|^2\right) \qquad (13)$$

If $g(x) = -k'(x)$, then $m_{h,G}(y) = y_1 - y_0$ is in the gradient direction. The iterative process stops when $\|y_1 - y_0\| < \varepsilon$. In Eq.(13) it is possible to notice that the maximum area where the target can be correctly localized is the kernel size. For this reason, if the center of the object shifts more than this size in two consecutive frames, the MS vector is no more correlated with the object itself and therefore the track is likely to be lost (Maggio, Cavallaro, 2005).

3 PROPOSED METHOD

3.1 The Tracker Framework of MSPFU

We can divide the proposed tracker into seven main steps as Figure.1 shows. The first step which is the initialization stage assigns one particle filter tracker for each target. These particle filters will track corresponding target independently in the latter video. The second step propagates each particle using proposal distribution according to Eq.(5). The third step applies MS independently to each particle for every particle filter tracker until all particles have reached a stable position. The fourth step calculates the weight of each particle filter using the Bhattacharryya coefficients as Eq.(10). The fifth step calculates the weighted average to obtain the best state as Eq.(11) for each target. The sixth step updates each target model according to Eq.(15). Finally, the seventh step re-samples the particles according to the weights of particle. Again, go to the second step to propagate particles into next time or next frame and begin a recursive process for tracking. Different from TSHT (Maggio, Cavallaro, 2005), we add target model update process after getting the target state. Another difference is we resample particles before propagation process.

3.2 Dynamic Model

The proposed particle filter tracker consists of an initialization of the target model and a sequential Monte Carlo implementation of a Bayesian filtering for the stochastic tracking system. In each iteration, the particle filter tracking algorithm consists of two steps: prediction and update. The state of the particle filter is defined as $\mathrm{x} = \{x, y\}$, where x, y indicate the location of the target. In the prediction stage, the samples in the state space are propagated through a dynamic model. We use the following second order autoregressive model (Cai, Nando, 2006):

$$x_k = Ax_{k\text{-}1} + Bx_{k\text{-}2} + CN(0,1) \qquad (14)$$

where $\{A, B, C\}$ are the coefficients, and $N(0,1)$ is a Gaussian noise with zero mean and standard deviation of one. This dynamic model uses the historical data to predict the current state value. The current state x_k only depends on the previous states with a deterministic mapping function and a stochastic disturbance.

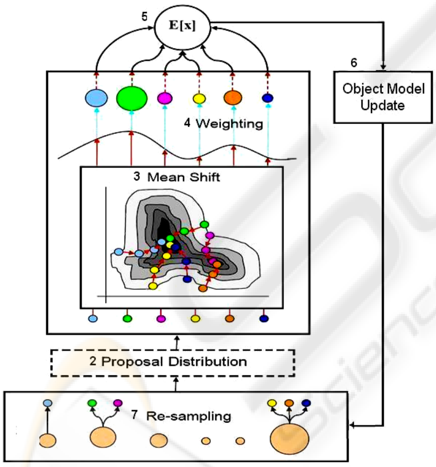


Figure 1: Schematic representation of our method.

3.3 Target Model Update

Illumination conditions and the visual angles can change the target appearance. For multi-target tracking task, mutual occlusion of objects is a frequent problem, which will change target appearance largely. In occlusion situation, the original target model can not describe the target appearance correctly. Still using the original target model in later tracking will seriously influence the quality of the color-based particle filter. This tracker may drift to other nearby target with the similar color or similar appearance. Updating target model is important and necessary for multi-target tracking. To describe the target appearance more effectively, we adaptively update the target model during tracking process. The update of the target model belonging to object m is implemented by the following equation (Nummiaro, Koller, 2002)

$$q_k^m = (1-\alpha_h) q_{k\text{-}1}^m + \alpha_h q_{k,E}^m \qquad (15)$$

for each bin, where α_h weighs the contribution of the mean state histogram $q_{k,E}^m$ of particles belonging to target m to the history target model $q_{k\text{-}1}^m$.

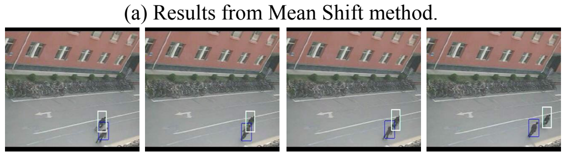
4 EXPERIMENTAL RESULTS

The proposed particle filter based tracker MSPFU has been implemented in Visual C++ and tested on a 3.2GHz Pentium4 PC with 512MB memory. It has been applied to a variety of tracking scenarios for multi-target tracking.

4.1 Robust to Partial Occlusion

The first experiment will analyse the tracking performance when multiple targets partial occlude each other. The video comes from a campus scene. The image size of the sequence is 320×240 with 25 frames per second. In this sequence, two persons move independently first, occlude each other and then depart. They have similar color and shape. We compared our method MSPFU with Mean Shift method (Comaniciu, Ramesh, 2003) using the same target model and initialization. Here we also add target model update to Mean Shift algorithm. In our tracking system MSPFU, we set the parameters A, B, C in Eq.(14) as 2, -1 and 16, and set α_h as 0.1. These values are fixed in our following experiments. Figure.2 shows the results of key frame in this video.

(a) Results from Mean Shift method.



(b) Results from Our method MSPFU.

Figure 2: Comparison of tracking performance between MS and our method on an outdoor campus video.

Figure.2.(a) demonstrates the results of Mean Shift tracking, which shows one tracker drift to another when the two persons occlude each other. Figure.2.(b) gives the results of our method, which can maintain tracking and correct identities although the two persons are similar in color and shape.

4.2 Target Model Update in Serious Occlusion Situation

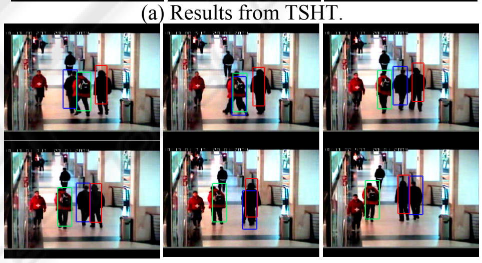
This experiment aims to analyse the multi-target traking performance for serious occlusion. The computational complexity and tracking accuracy of our method and some existed methods are compared. Here, we used a public test sequence named "ThreePastShop2cor.mpg" and the relative ground truth file obtained from website (Http://, 2004). The image sizes are 384×288 pixels, 25 frames per second. Three persons move in this video. We initialize three persons on frame No.400 with colored rectangle boxes according to the ground truth file. The left person is labeled A with blue box, the middle person is labeled B with green box and the right person labeled C with red box. In this video, sometimes A and B, A and C are seriously occluded, and A and C have same color, which is difficult to maintain correct tracking.

First, we compare TSHT method (Maggio, Cavallaro, 2005) with our method. TSHT embeds Mean Shift into particle filter without target model update process. We assign 1000 particle samples for each target for TSHT. To compare the tracking performance on the same baseline, we use same initial target model and dynamic model. Figure3.(a) gives the results of TSHT method with 1000 particles for each target, which shows several errors especially when the two targets are seriously occluded. From the results, we can see that the appearance of target is changed largely when it is occluded by other objects. But TSHT method still uses the initial target model to track, which makes tracker A drift to C in the second resulted image and C drift to B in the fourth resulted image. In this situation, assigning more particles for each target cannot maintain correct tracking. Figure 3.(b) shows the results of our method MSPFU, which can maintain correct tracking although the two persons are seriously occluded and the two persons have similar color and shape. Our method uses only 40 particles for each target in initialization stage.

Second, as for the computational complexity, we compare our method MSPFU with the PF. We add target model update process for PF method. In our experiment, PF method use at least 100 particles for each target to maintain correct tracking and the average processing time for each frame is 722 ms. Our tracking system MSPFU uses only 40 particles for each target in initialization stage and the average processing time for each frame is 436 ms, which can track multi-target quickly.

In above experiments, we compare the computational complexity in tracking multiple targets in terms of the number of particles. To compare the tracking accuracy, we consider the accuracy of target center position. The distance between the real tracked center position of target and the ground truth is calculated to measure the tracking accuracy for PF and MSPFU.

(a) Results from TSHT.



(b) Results from Our method MSPFU.

Figure 3: Comparison of tracking performance between TSHT and our method PFMSU on a public open video.

Figure4 shows the accuracy results of tracking accuracy with 40 particles for each target from frame No.400 to frame No.700 every four frames. The horizontal axis means the No. of frame and the vertical axis means the distance. The smaller the distance is, the higher the tracking accuracy is. Method MSPFU can track multi-target correctly with small distance from the ground truth, while method PF is failure in tracking target A and target C during this sequence. Figure5 gives the results of tracking accuracy with 100 particles for each target. We can see both of MSPFU and PF can track multi-target correctly here, while method MSPFU has better tracking accuracy on target B than method PF.

We also give the average distance on the test frames. Table1 is average distance result of tracking, where PN means particle number, TPF means processing time per frame, AD_A means average distance of target A and CT_A means if target A is correctly tracked or not. From the result of table1, we can see using more particles will take more

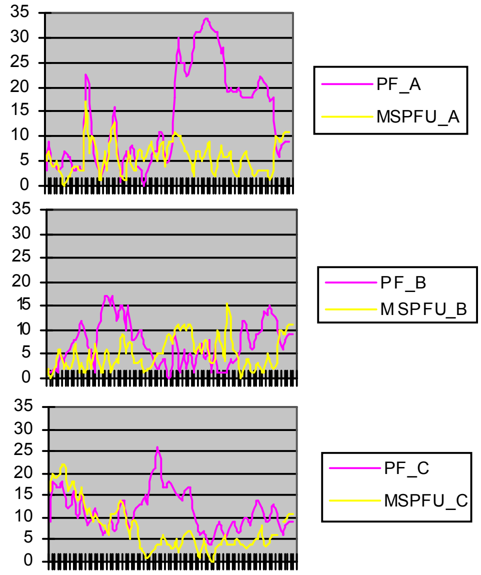


Figure 4: Tracking accuracy results with 40 particles.

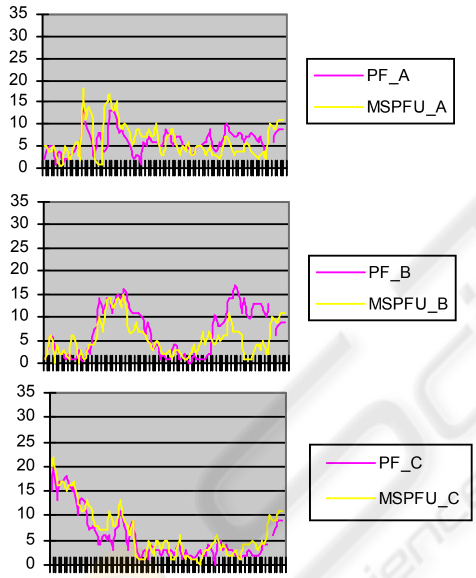


Figure 5: Tracking accuracy results with 100 particles.

tracking time. Method MSPFU can keep correct tracking with less particles than method PF. The average distance of method MSPFU with 100 particles is smaller than that of method PF, which shows the method MSPFU have better tracking accuracy.

5 CONCLUSIONS

We presented a novel multi-target tracking algorithm combining Particle Filter and Mean Shift with an adaptive target model update process. The Mean Shift is inserted into Particle Filter framework in order to make each particle independent and therefore more flexible to local conditions, thus reduce the particle number in initialization stage. In our paper, the adaptive target model update process is important to solve the problem of object occlusion and illumination changes. Experimental results showed that the proposed algorithm is faster and more accurate than PF and TSHT method, and more reliable than Mean Shift. From the experiment, we find the computational complexity is related by the number of particles and the target model. Future work includes tracking a variable number of targets in a dynamic scene and investigating new target model.

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Table 1: Results of tracking accuracy on video two with 40 and 100 particles.

PN	Method	TPF(ms)	AD_A	CT_A	AD_B	CT_B	AD_C	CT_C
40	PF	400	14	False	7	Ok	11	False
40	MSPFU	436	5	Ok	4	Ok	7	Ok
100	PF	722	5	Ok	6	Ok	5	Ok
100	MSPFU	743	5	Ok	4	Ok	6	Ok