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Visual Object Tracking Based on Mean-shift and Particle-Kalman Filter

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Abstract

Even though many algorithms have been developed and many applications of object tracking have been made, object tracking is still considered as a difficult task to accomplish. The existence of several problems such as illumination variation, tracking non-rigid object, non-linear motion, occlusion, and requirement of real time implementation has made tracking as one of the challenging tasks in computer vision. In this paper a tracking algorithm which combines mean-shift and particle-Kalman filter is proposed to overcome above mentioned problems. The purpose of this combination is to draw each algorithm's strength points and cover each algorithms drawbacks. In the proposed method, mean-shift is used as master tracker when the target object is not occluded. When occlusion is occurred or the mean-shift tracking result is not convincing, particle-Kalman filter will act as master tracker to improve the tracking results. Experimental results of the proposed method show desirable performance in tracking objects under several above mentioned problems.

Keywords: Visual Object Tracking; Mean-shift; Particle-Kalman Filter;

1. Introduction

In recent years, visual object tracking has been receiving a huge interest in the field of computer vision research. It plays important roles in many applications such as automatic traffic monitoring [1], video surveillance [2], vehicle control system [3], robot vision [4], and behavior analysis [5]. Even though many algorithms and application of visual object tracking have been made, visual object tracking is still a challenging task to accomplish. There are several difficulties that could arise in object tracking due to several reasons, including some factors come from the environment, such as cluttered background and illumination variation, the characteristics of the target object itself, or the interaction between the objects.

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Many algorithms have been made for visual object tracking. Zhang categorized these visual object tracking algorithms into two categories, deterministic method and probabilistic method[6]. One of the most commonly used deterministic methods is mean-shift[7,8,9]. Mean-shift is widely used because of its robustness against light partial occlusion and its low complexity algorithm which makes the computational become faster, more efficient, and suitable for real time implementation. However it has some drawbacks such as its inability in tracking fast motion object and poor performance in occlusion handling. The second category of visual object tracking methods is probability method. Some typical examples of this probability method is Kalman filter[10,11] and particle filter algorithm[12,13]. Many researchers utilize Kalman filter because of its easiness to formulate and implement, especially for real time tracking. Moreover the prediction equation of Kalman filter is often utilized to predict the location of the target object with linear motion when it is occluded by other objects. Therefore, Kalman filter is often referred as the best Gaussian or linear system estimator[14]. However in real world, most of the movements usually are non-Gaussian processes[15]. This might bring a problem in Kalman-based visual object tracking when the movement of the target object is not linear, for example when the target object changes its attitude or velocity abruptly. Another example of probabilistic method is Particle filter. Unlike Kalman filter, particle filter is able to deal with non-Gaussian problem[16]. However, the major drawback of particle filter lies on the requirement of vast particles number as samples. This significant number of particles induces a huge computational complexity and affects the tracking performance speed, especially if it is applied for multiple object tracking when vast number of particles are employed for each target object. Therefore, particle filter usually is not suitable for real-time implementation.

2. Previous Works

Based on the analysis of several tracking algorithms above, it can be concluded that utilizing only single algorithm for visual object tracking is considered as inefficient because every algorithm has their limitations. Based on this motivation, many researchers often utilize a combination of several algorithms to extract strong points of each algorithm and cover each algorithms drawbacks. Iraei[17], Zhao[18], and Zhou[19] combined mean-shift and Kalman filter algorithm to track object under occlusion. Kalman filter algorithm is utilized to update the estimate location of the target object when occlusion occurred. The experiment results show that the combination of mean-shift and particle filter is robust in dealing with occlusion. However, because Kalman filter is used as the predictor when the object is occluded, the system only able to deal with linear motion. Chu[20], Qiao[21], Maggio[16], and Chen[22] proposed a method by combining particle filter with mean-shift. To enhance the particle filters performance, mean-shift is applied into each particle to shift them towards a close local maximum. By this way, a few condensed particle set with fewer particles can be obtained and the divergence problem can be decreased. Chen[22]has proven that mean-shift-particle filter is robust in dealing with fast moving object and occlusion by using only few particles. However, even though the number of particles is reduced, the tracking speed is still quite slow because of the required iterations of mean-shift for each particle. Furthermore, the particle set usually is too concentrated as a result of mean-shift algorithm applied to each particle. This condition may lead to tracking failure particularly when the system needs to track the object re-appeared after severe or full occlusion occurred.

Another method that combines two conventional algorithms is particle-Kalman filter. The main concept of particle Kalman filter is based on phenomenon of most cases in video tracking, where the target object is moving under linear or Gausssian motion in global view whereas non-linear motion is usually limited in the local view[23]. Therefore Kalman filter is employed to perform estimate global motion and particle filter is employed to perform local estimation to cope with non-linear motion in local view. In particle Kalman filter (PKF), the linearity of Kalman filter is implemented for every particle to obtain more condensed particle and each particle deals with non-linearity problem. In this way, the number of particles can be significantly reduced without any iteration addition. Hence, the speed of the system can be increased significantly compare to the combination of mean-shift and particle filter.

In order to cope with several tracking algorithms that have been mentioned above, in this paper an object tracking algorithm that combines mean-shift and particle-kalman filter is proposed. In the proposed method, mean-shift is used as master tracker when the target object is not occluded. When occlusion is occurred or the mean-shift tracking result is not convincing, particle-Kalman filter will act as master tracker to improve the tracking results.

3. The Proposed Method: Combination of Meanshift and Particle-Kalman Filter

In order to make the system more efficient, in the proposed method mean-shift is combined with particle-Kalman filter to deal with non-occluded object tracking. Conversely when the tracking result of mean-shift is not convincing, particle-Kalman filter is used to deal with occlusion and non-linear motion problem. In this section the flowchart diagram of the proposed method is presented. Afterwards, each step in the proposed method will be explained in detail.

3.1. Model Initialization

First, the target object is selected manually from the first frame of the video sequence. The target object is selected by cropping the region of interest to determine the initial position of the target object. The target object is represented by a rectangular area.

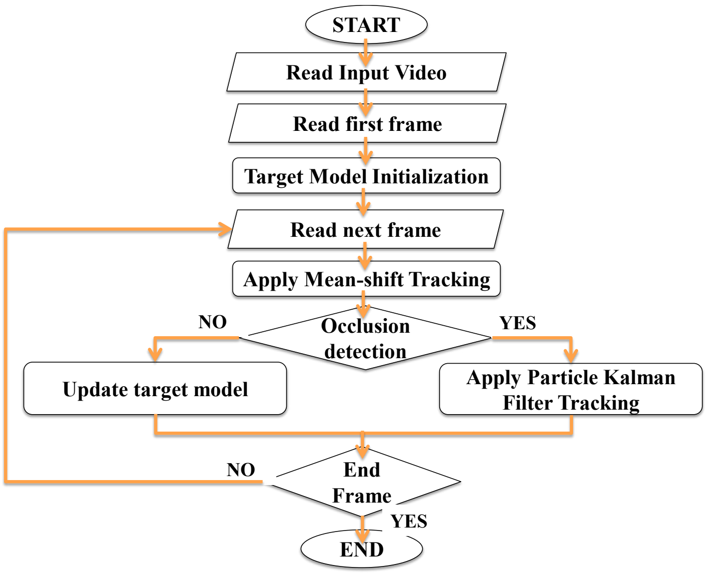


Fig. 1: Main Flowchart of The Proposed Method

Instead of using common color histogram, a weighted histogram proposed by Commaniciu et all in 2003 [24] is utilized in order to make the distribution more reliable and reduce the effect of the background. Moreover in order to reduce the effect of illumination variation, 8x8x4 HSV color space is utilized to build the weighted histogram. The color distribution of the target model $q(u)$ is represented as shown in the equation (1). Where x_c defines the center of the target candidate's rectangular area, C defines the normalized coefficients, and h defines the normalizing constant (e.g. $h = \sqrt{H_x^2 + H_y^2}$).

$$q(u) = C \sum_{i=1}^{n} \left(\left\| \frac{x_c - x_i}{h} \right\| \right)^2 \delta(b(x_i) - u) \tag{1}$$

3.2. Apply Mean-shift Algorithm

After initialize the target model, the system will start to track the target object. In our system, mean-shift is utilized as the master tracker until result is not convincing which usually happened because of occlusion and abrupt object motion changes. Meanshift is used as the main tracker when no occlusion occurred because of following reasons:

1. Both mean-shift and particle filter work well in tracking non-occluded object with constant velocity. However compare to mean-shift, particle filter has higher complexity algorithm which may cause slow system performance. Even when the particle filter is combined with Kalman filter, mean-shift still works more efficient to track non-occluded object with linear motion.
2. Mean-shift is used to improve the speed performance of the particle-kalman filter.

In the next step, the mean-shifts tracking result is compared to the target model to check the accuracy of the tracking results. There are several problems that can affect the tracking results of mean-shift algorithm :

1. Target object moves in high speed velocity or increase its velocity abruptly.
2. Target object is severely occluded

In order to make the system robust against occlusion and to improve the tracking result when dealing with fast moving object, in our system, Particle-Kalman filter is employed whenever the tracking result of mean-shift is not convincing. To check the accuracy of mean-shift tracking result, a similarity function that compares the tracking result of mean-shift with the target model is used. The tracking result of mean-shift is considered as accurate if the similarity function fulfills the requirement below

$$SIM(T_0, C_0) \geq Th_1 \tag{2}$$

where To and Co are defined as target object and candidate object (detected object) respectively. Th_1 is the predefined threshold which is used to check the accuracy of mean-shift tracking result. The similarity function $SIM(To, Co)$ is calculated using Bhattacharyya coefficient to compute the distance similarity of target models and detected objects color distributions, which is denoted by

$$SIM(T_0, C_0) = \sum_{u=1}^{b} \sqrt{H_{T0}(u) * H_{C0}(u)} \tag{3}$$

H_{T0} and H_{C0} are the color distributions of target model and detected object. b denoted as total number of histogram bins. In our experiment we choose 0.8 as the value of occlusion detection threshold.

3.3. Apply Particle-Kalman Filter

When the tracking result of mean-shift is not convincing, the main tracker of proposed method will be switched into particle-Kalman filter. The principle of Kalman filter is combined with particle filter in order to increase the speed of particles convergence and reduce the number of particles in the particle set. Particle-Kalman filter is utilized in the proposed method to deal with occlusion and non-linear motion problem.

3.4. Update Target Model

The target objects appearance will change over time due to changing in illumination, objects pose, and viewing angle. In order to overcome this problem, it is important to adapt the target model over time. In our method, the color distribution of target model is adapted at every frame by following equation

$$q_k^{(u)} = (1 - \alpha) q_{k-1}^{(u)} + \alpha p_{E(X_k)}^{u} \tag{4}$$

where α is a factor that determines how the color distribution of current detected object $p^{u}_{E(X_k)}$ influenced the target model at current frame. Where in our method the value of $\alpha = 0.05$. In order to ensure that the target model will not be updated when the tracker losted the target object or when the target object is occluded, the target model only will be updated when mean-shift acts as the main tracker, conversely when PKF acts as the main tracker, the target model will not be updated.

4. Experiment Results

In this section, the experiment results of proposed method and the comparison with other methods such as Mean-shift-Kalman filter algorithm (MKF), Mean-shift-particle filter (MPF), and original color based particle filter (PF) are presented. The robustness and efficiency of the proposed method are evaluated qualitatively and quantitatively. The proposed method and other comparison algorithms have been implemented on MATLAB R2013a platform. All experiments were performed on an Intel Core i5 @1.70 GHz CPU with 6 GB of RAM and 1 GB Intel HD Graphics. Eight videos are used for single object tracking experiment.

4.1. *Qualitative Evaluation*

For qualitative evaluation, the proposed method and other comparator algorithms are tested on eight challenging sequences for three main experiments, i.e. : non-linear motion, severe partial occlusion, and full occlusion.

4.1.1. *Non-linear motion*

In order to test the robustness of our method against non-linear motion we used video sequence CarChase_1 from dataset[25]. In the following experiments results, we compare the results of proposed method with combination algorithm of Mean-shift and Kalman Fiter (MKF). The video sequence CarChase_1 contains an object (car) which moves with high speed velocity. In order to deal with this problem, in MKF, Kalman filter is used to predict the position of the target object when the tracking results of Mean-shift is not convincing. One of the Kalman filter drawbacks is Kalman filter only can deal with linear motion. Therefore, when the target object changes its direction abruptly, MKF fails to track the position of the target object. On the contrary, the proposed method is robust in tracking high speed moving object with non-linear motion. Similar to MKF, first mean-shift is utilized as the main tracker in order to simplify the algorithms complexity and boost the system speed performance. When the target object moves with non-linear motion, particle-kalman filter which can deal with non-linear tracking problem is utilized to improve the tracking results. The tracking results can be seen in table 1

Table 1: Tracking results for non-linear motion

Method	Frame = 850	Frame = 880	Frame = 890	Frame = 910
MKF				
Proposed Method				

4.1.2. Severe Partial Occlusion

To test the robustness of our proposed method against severe partial occlusion, our own dataset is used. We compare the tracking results of our proposed method with tracking results of two algorithm combinations, i.e. Mean-shift-Kalman filter (MKF) and Mean-shift-particle filter (MPF). The yellow man is chosen as the target object in the video sequence. The tracking results can be seen in Table 2.

Table 2: Tracking results for severe partial occlusion

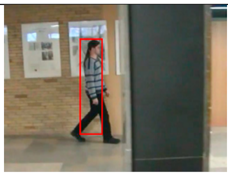
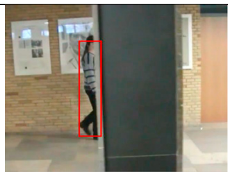
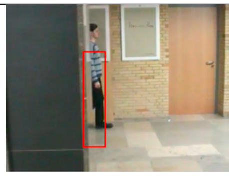
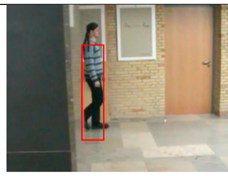
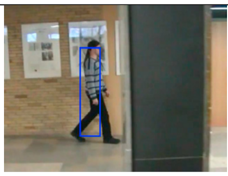
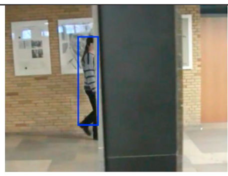
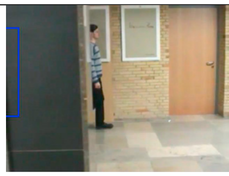
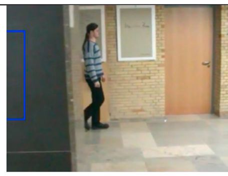
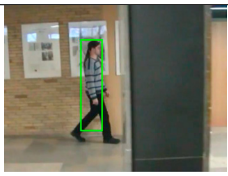
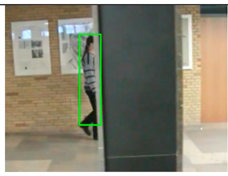
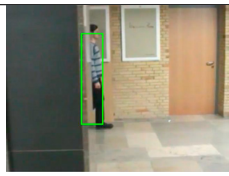
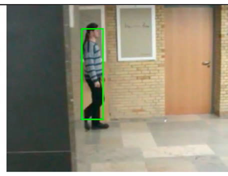
Method	Frame = 110	Frame = 150	Frame = 180	Frame = 200
MKF				
MPF				
Proposed Method				

The experiment results in Table 2 show that both mean-shift-particle filter (MPF) and proposed method are able to track the target object successfully whereas mean-shift-kalman filter (MKF) failed to track the target object. From Table 2 it can be seen that at first the target object stands still on its position. However, when the target object is severely occluded by the blue man, the target object is moving forward abruptly which indicates a non-linear motion. In combination of mean-shift and Kalman filter (MKF), when the target object is severely occluded, mean-shift is unable to track the target object, as mentioned before that one of mean-shift drawback is its inability to track object under severe occlusion. Therefore, in order to cope with this problem, Kalman filter is employed to predict the position of the target object. However because Kalman filter only can deal with linear motion and the object moves with non-linear motion, mean-shift-Kalman filter fails to track the target object. Experiment results show that both mean-shift-particle filter and our proposed method are robust to cope with severe partial occlusion and non-linear motion.

4.1.3. Full Occlusion

To prove the robustness of our proposed method against full occlusion, video sequence Vid_F_person_fully_occluded[26] is used. Our proposed method is compared with mean-shift-kalman filter and mean-shift-particle filter (MPF). In the data set we used, the target object is moving with linear motion and is fully occluded by the wall. Experiment results show that both mean-shift-Kalman filter (MKF) and our proposed method can successfully track the target object that reappear after full occlusion occurred. Mean-shift-Kalman (MKF) can track the target object successfully because the target object is moving with linear motion. When the target object is occluded, Kalman filter is employed as the main tracker to predict the location of the target object during occlusion. Hence, when the target object is reappear, MKF can track the target object successfully. On the contrary, failed in tracking the target object under full occlusion. As discussed before, it happens because the particle distribution in MPF are too concentrated, hence when full occlusion occurred, the particles are unable to track the target object when it is reappeared as shown in table 3.

Table 3: Tracking results for full occlusion

Method	Frame = 165	Frame = 170	Frame = 187	Frame = 190
MKF				
MPF				
Proposed Method				

4.2. *Quantitative Evaluation*

In order to analyze the performance of our tracking system quantitatively, a set of metrics is utilized to compute the accuracy of the proposed method tracking system with other algorithms[27]. The evaluation metrics work by comparing the results of the tracking systems to a set of ground truth data. In our experiments, all metrics are computed for eight video datasets[25 28 26]. The information about all video datasets used for performance evaluation are presented in the Table 4.

Three evaluation metrics are used to evaluate the performances of the proposed method and other comparator algorithms quantitatively, i.e. Tracker Detection Rate, accuracy, and system speed performance[27]. From the performance evaluation result than can be seen in Table 5, it shows that our proposed method has higher score in accuracy and detection rate in almost every dataset compare to MKF and MPF algorithms. Moreover for the speed performance, we compare our proposed method with conventional particle filter (100 particles) and MPF algorithm (20 particles). The experiment result shows that the proposed method works significantly faster than conventional particle filter because it uses less particle and also faster than MPF algorithm because no meanshift iteration is done for each particle.

5. Conclusion and Future Works

In this paper, a robust visual tracking algorithm which combines several conventional algorithms such as Mean-shift, Kalman filter, and Particle filter is developed. The purpose of this combination is to draw the strength points of each algorithms in order to cover each algorithms drawbacks. In the proposed method mean-shift is used as the main tracker when there is no occlusion occurred. Conversely when occlusion occurred or the mean-shift tracking result is not convincing, particle-Kalman filter (PKF) is used as the main tracker to recover the tracking results. In PKF, Kalman filter is combined with particle filter in order to increase the speed of particles convergence to reduce the number of particles. In this way the speed of the system can be increased significantly. From the experiment results it is proven that the proposed method is able to deal with several tracking problems such as non-rigid object, non-linear motion, and occlusion. Moreover, it is also proven that the proposed method is more suitable for real time implementation compare to other comparator algorithms.

However, because the proposed method only used color as the tracking feature, the system may fail when the target object is occluded by other object which has similar color distribution. Therefore, in order to improve the performance of the proposed method, multi features can be utilized to represent the target model.

Table 4: Video Datasets for Single Object Tracking Performance Evaluation

Video Name	Number of Frames	Attributes	Source
CarChase_1	350	Full occlusion, Ilumination Variation, Non-linear motion	Kalal benchmark [25]
CarChase_2	1000	Full occlusion, Ilumination Variation, Non-linear motion	Kalal benchmark [25]
David3	252	Deformation, light partial occlusion	tracker_benchmark_v1 [28]
Woman	550	Deformation, light partial occlusion, Ilumination variation	tracker_benchmark_v1 [28]
Vid_F_person_fully_occluded	545	Deformation, full occlusion, severe partial occlusion, ilumination variation	BoBot benchmark [26]
Vid_I_person_crossing	1222	Deformation, full occlusion, ilumination variation	BoBot benchmark [26]
Jogging	306	Full occlusion, ilumination variation	tracker_benchmark_v1 [28]
Vid_J_person_floor	467	ilumination variation, severe partial occlusion, non-linear motion	BoBot benchmark [26]

Table 5: Performance Evaluation Results

Video Name	Tracker Detection Rate			Accuracy			Speed performance (second)		
	MKF	MPF	Prop. Method	MKF	MPF	Prop. Method	Conv. PF (100 particles)	MPF (20 particles)	Prop. Method (20 particles)
CarChase_1	0.6685	0.8286	0.9143	0.7286	0.8714	0.98	0.911	0.4121	0.0873
CarChase_2	0.722	0.860	0.943	0.762	0.91	0.9930	0.5267	0.2775	0.074
David3	1	1	1	1	1	1	0.7377	0.3768	0.065
Woman	0.9527	0.9709	0.9836	0.9527	0.9709	0.9836	0.4637	0.2299	0.0803
Vid_F_person_fully_occluded	0.8073	0.4771	0.9101	0.8807	0.4991	0.9834	2.4170	1.3299	0.1458
Vid_I_person_crossing	0.6735	0.7684	0.9525	0.6735	0.7684	0.9525	2.2294	0.8671	0.0712
Jogging	1	0.7876	1	1	0.7876	1	0.4902	0.2236	0.0441
Vid_J_person_floor	0.5567	0.8951	1	0.5567	0.8951	1	1.1484	0.4931	0.0919

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