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E-mail :
editor.ijpast@gmail.com
editor@ijpast.in

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Observing Occlusion's Impact on Kernel-Based Object Tracking in Virtual Reality

G VENGALARAO[1] , K ASHOK KUMAR[2]

Abstract

When it comes to object tracking in computer vision, occlusion management is one of the most researched challenges. Several publications have claimed that Kalman filter, Particle filter, and Mean Shift tracking can successfully deal with occlusion. However, relatively little testing was done on task-oriented video. This article tested the tracking algorithms using six simulated films taking into account a variety of occlusion circumstances in order to better understand their true capabilities. The effectiveness of a tracking system is measured by its SFDA, or Sequence Frame Detection Accuracy. The findings confirm the claims of many prior publications that Mean shift tracker will utterly fail in the presence of full occlusion. The SFDA score was between 0.3 and 0.4 for both the Kalman filter and the Particle filter tracker. This experiment shows that Particle filter tracker can't keep up with objects that move at will. Frame Detection Accuracy (FDA) graphs are used to examine the impact of occlusion on individual trackers.

Key words : ***Topics covered include Occlusion Handling, Object Tracking, and Computer Vision.***

Introduction

When it comes to computer vision, occlusion handling presents a significant obstacle for object tracking. When a tracked object temporarily disappears from camera views without leaving the ROI, this phenomenon is known as occlusion. In video surveillance, the region of interest refers to the portion of a video frame that is of interest to the user.There are three causes of occlusions. First, occlusion occurs when an item is hidden from view by another structure, such as a wall or a piece of furniture [9]. Second, occlusion may occur if the tracked item is occluded by other moving foreground objects [2, 7]. Finally, occlusion occurs when the tracked objects turn away from the camera, obscuring the track features [7]. When trying to follow a person using facial recognition software, having them swivel their head might be a major hindrance. Self-occlusion describes this behaviour.

Several approaches have been presented for tracking occlusion in carefully chosen video samples. Videos are either recorded by the authors themselves or taken from publicly available benchmark datasets like PETS [14] and ETISEO [5]. The performance of the proposed tracking approach is well represented in these video datasets. However, the video's complicated environment, including shadow, lighting variations, and a revolving backdrop, may make it difficult to assess the tracking algorithms' true effectiveness. As a result, we suggest doing the tests using simulated video data. Taylor et al. [16] claim that simulated video data is suitable for revealing which

Assistant professor[1,2]
DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING
P.B.R.VISVODAYA INSTITUTE OF TECHNOLOGY & SCIENCE
S.P.S.R NELLORE DIST, A.P , INDIA , KAVALI-524201

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algorithms perform best under certain conditions. In addition, synthetic video may serve as a reliable golstandard against which actual results can be measured. The perfect setting, free of background noise and other interruptions, may be generated in such simulation movies. It's possible that the tested tracking techniques' true performance would be reflected in the confined environment findings. Occlusion analysis in simulation films will also be simplified because to the ability to manipulate the setting and the way in which objects interact. Here is how the rest of the paper is structured. In Chapter 2, we examine relevant works that have come before. Based on research done before, this report employs three different tracking strategies. The experiment's video simulations are discussed in Section 3. The experimental and tracking measurement findings are presented in sections 4 and 5, respectively. Section 6 focuses on what comes next. The paper is finished with Section 7.

Earlier Works

Point tracking, silhouette tracking, and kernel-based tracking are the three main types of tracking techniques, as described by Yilmaz et al. [16]. Minimal computational expense is incurred while tracking points, but precision is sacrificed. significant precision and the ability to handle transformable tracking objects come with a significant computational cost in silhouette tracking. Since kernel-based tracking may give great precision at a cheaper computational cost than silhouette-based tracking, it has found widespread application. In kernel-based tracking, a plethora of approaches have been presented. Kernel-based tracking has been explored in depth by Comaneci et al. [4]. Most recent efforts have concentrated on Kalman Filter, Particle Filter, and Mean Shift tracking, three of the most well-known kernel-based tracking algorithms. Mean Shift-based trackers for deriving target object candidates based on appearance model similarity have been developed by Comaneci et al. [5] and Yilmaz [22]. Their findings demonstrate that the Mean Shift tracker can withstand challenges like as partial occlusion, noise in the background, changes in target size, and 3D rotations. The performance of the Mean Shift tracker in cases of complete occlusion and objects with arbitrary trajectories was not explored by Comaneci et al. [5] and Yilmaz [22]. Therefore, in this paper's studies, we put these three tracking approaches to the test. Researchers Marabi&Javaid [15] and Wang et al. [20] tried out the Kalman Filter tracker on footage from the actual world. Both tests demonstrated that the system performed well despite the presence of noise, shadows, and varying light levels. The Kalman filter tracker is also said to be computationally cheap. Objects having unpredictable paths are not taken into account in these tests of tracking technology. Particle filters allow for accurate tracking of non-stationary objects, even those with a non-linear and non-Gaussian trajectory [3]. Liang et al. [14] coupled Particle Filter tracker with color and form model to track objects in video sequences, while Chuo et al. [3] utilized Particle Filter tracker with pictures' grey level model to follow the moving item. Many of these earlier efforts [3, 5, 14, 15, 20, 22] only provided their findings as still photos of video sequences demonstrating the occurrences of effective tracking, as noted in the assessments of these works. Neither the accuracy of the tracking studies nor a statistical comparison to other tracking techniques were mentioned. Therefore, in this study, we will undertake a series of experiments to carefully analyse the performance of each tracker by measuring their accuracy on a set of simulated video sequences. Additionally, writers that tested their methods with their own recorded video seldom elaborated on the limitations of their approach. Many people think the video samples they utilized in their experiment are too complicated to analyse, and that the alternative approaches they presented are more suited to practical use cases. Normal video recordings suffer from issues including ambient noise, shadows, and lighting alterations. Thus, we use simulated video sequences to regulate the video scene in order to decrease complexity in video samples. The experimental findings may more accurately represent the trackers' true capacity to handle occlusion if the scenes are put up in a controlled manner.

Evidence from video cameras

Six different simulated video sequences with moving objects are produced. Table 1 displays the titles and descriptions of the videos. The simulation was programmed in Visual C++ and OpenGL. Figure 1 depicts the predetermined video sequence of video label A1, which replicates a single-coloured ball moving from the left, rolling over to the right, and leaving the video frame. The video's simulation ensures that the ball always travels at the same rate and in the same direction. In Figure 2, we have yet another simulated video sequence in which a single-coloured ball travels towards the centre of the screen from the left, only to reverse course and leave the frame on the right. This movie is meant to simulate A2 random motion in order to evaluate the performance of tracking algorithms.

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Table 1: Video label and description

Label	Description
A1	Moving ball with constant speed and direction
A2	Moving ball with constant speed and arbitrary direction
A3	Moving ball with constant speed and direction with full occlusion
A4	Moving ball with constant speed and direction with partial occlusion
A5	Moving ball with constant speed and arbitrary direction with full occlusion
A6	Moving ball with constant speed and arbitrary direction with partial occlusion

An obstacle is placed in the middle of video frame to represent occlusion in simulation video. In the experiments, two types of occlusions are concerned which included full occlusion and partial occlusion. Figure 3 shows a big rectangle is placed in the middle of the video frame in a video with a ball moves at constant speed and direction. This video labelled as A3, is used to test how an object tracking method could handle moving object after full occlusion. Figure 4 shows some video frames of a video sequence of video label A4 for testing partial occlusion at constant speed and direction. Video with partial and full occlusion are also created for moving object with arbitrary direction change as described of video label A5 and A6.

Fig. 1. Video Frame (a) Frame no. 1, (b) Frame no 10, (c) frame no. 22, (d) frame no. 30 and (e) frame no. 50 of simulation video A1.

Fig. 2. Video Frame (a) Frame no. 1, (b) Frame no 10, (c) frame no. 22, (d) frame no. 30 and (e) frame no. 50 of simulation video A2.

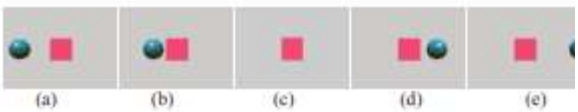

Fig. 3. Video Frame (a) Frame no. 1, (b) Frame no 10, (c) frame no. 22, (d) frame no. 30 and (e) frame no. 50 of simulation video A3.

Fig. 4. Video Frame (a) Frame no. 1, (b) Frame no 10, (c) frame no. 22, (d) frame no. 30 and (e) frame no. 50 of simulation video A4.

Tracking Performance Measurement

Two tracking performance measurement methods are used in this paper. Both measurement methods are based on the framework by Kasturi et al. [10], which are highly cited protocol for performance evaluation of object detection and tracking in video sequences (other papers agree such statement). The fist method is the Sequence Frame Detection Accuracy (SFDA) as denoted in equation (1) and the second method is Frame Detection Accuracy as expressed in equation (2).

measurements measure the number of objects detected and missed detection, false positives and spatial alignment of the system output and ground-truth object.

$$SFDA = \frac{\sum_{t=1}^{t=Nframce} FDA(t)}{\sum_{t=1}^{t=Nframce} \exists(N_G^{(t)}\ or\ N_D^{(t)})}$$

$$FDA(t) = \frac{Overlap\_Ratio}{\left[\frac{N_G^{(t)} + N_D^{(t)}}{2}\right]}$$

$$Overlap\_Ratio = \sum_{i=1}^{N_{mapped}^{(t)}} \frac{|G_i^{(t)} \cap D_i^{(t)}|}{|G_i^{(t)} \cup D_i^{(t)}|}$$

To calculate the result for both mentioned measurements, ground through is generated using object detection algorithm based on background subtraction [8]. The path of the moving object in video sequence A1, A3 and A5 are identical while A2, A4 and A6 share another similar path. Therefore, only two object movement ground truths are generated for verification of the tracking results.

Experimental Results

Experiments have been carried out to evaluate the performance of occlusion handling of the Kalman filter (KF) tracker, Particle filter (PF) tracker and Mean Shift (MS) tracker. The tracker algorithms in MATLAB script are modified and customized based on available sources to suit the experiments . The spatial information of the tracked object is written to text files. Tracking results of various tracker used for the experiments are shown in Table

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www.ijpast.in
Vol 12,Issuse 3 .July 2022

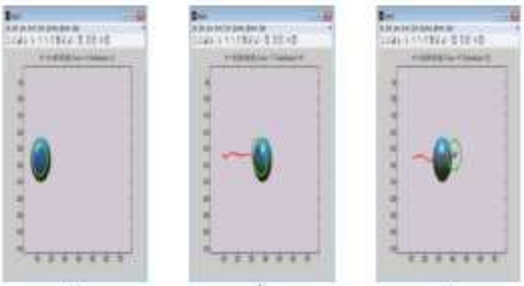
2. Kalman filter (KF) tracker used in the experiments is modified from Kashan pour [9]. The SFDA obtained from the tracking experiment using KF tracker is in between 0.3434 and 0.4677. The lowest SFDA score was obtained in video sequence A3 where full occlusion occurred.

Table 2: Tracking result (SFDA) for six simulation videos Video Sequence

Video Sequence	SFDA		
	KF	PF	MS
A1	0.4628	0.4725	0.5196
A2	0.4583	0.1606	0.6071
A3	0.3434	0.3473	0.0912
A4	0.3732	0.3567	0.4825
A5	0.4568	0.3701	0.3781
A6	0.4677	0.2616	0.5370
Average	**0.4270**	**0.3281**	**0.4359**

Particle filter (PF) tracker is used to track object in the same set of video sequences. The PF tracker used is based on Paris [16]. Based on the SFDA score in Table 2, the result of PF tracker is poorer than KF tracker. The lowest SFDA is achieved when performing PF tracker on video sequence A2. Based on observation, the PF tracker fails to detect the moving object in the video sequence A2 after frame number 22. A close examination found that the lost track of the object is due to a long period of consistent trajectory of the moving object before frame 22. Stretched consistent trajectory caused the distribution area of the particle become contracted and cover .

only a small area in the video frame. Therefore, when the trajectory of the object changed suddenly, the PF fail to track the moving object as shown in Figure 5



(a) (b) (c)

Fig. 5. Particle distribution: a) particles cover a large area at the initial state; b) when object trajectory remains consistent between frames, the particle area shrunk; c) particle area become so small and fail to detect the moving object change direction.

In conclusion, Bernhard's [1] Mean Shift (MS) tracker is finally, Bernhard's Mean Shift (MS) tracker [1] is utilized to evaluate MS tracker's efficacy. When an occlusion does not occur, the MS tracker returns the best possible result. The greatest SFDAs for video sequences A1 (0.5196) and A2 (0.6071) are indicative of this. In video frame A3, complete occlusion caused the SFDA of the MS tracker to plummet to a meagre 0.0912. Full occlusion was also seen in frame 22 of video sequence A4. At frame 23, however, the moving item does a U-turn back to its position before complete occlusion, allowing the tracker to once again acquire it. The SFDA result of the MS tracker is marginally lower for partial occlusion than for the A1 and A2 video sequences without occlusion. In comparison to other, more advanced tracking methods, such as Conte et al.'s [6] work, which used a similarity measurement of a matrix representation and an appearance model to follow a moving item in a dynamic scene, the average result attained in this research is subpar. Average SFDAs achieved by this article are 0.427 (KF), 0.328 (PF), and 0.436 (MS), whereas the average SFDAs acquired by Conte et al. [6] while testing their tracking approach using PETS2009 S2.L1 video sequences were 0.505. Due to differences in object, backdrop scene, and occlusion situation in the video sequences utilized, it is not fair to compare findings across publications. This paper's findings are applicable to the following section's discussion of occlusion's impact.

Occlusion's Impact

Table 2's SFDA gives a high-level overview of three distinct trackers' efficacy. The SFDA, however, gives only an overall average for all trackers. The Frame Detection Accuracy is compiled and analysed from frame 12 through frame 31 to examine the impact of occlusion in more detail. In both sequences A3 and A4, the whole moving item is still visible in frame 12. For video sequences A3 and A4, occlusion occurs at frame 13, whereas for sequences A5 and A6, it begins at frame 15 and frame 17, respectively. Figure 6 shows that following a complete occlusion in video sequence A3, the MS tracker was unable to resume detecting the moving object, whereas the KF and PF trackers were able to do so. Even when an occlusion is present in the video, the PF tracker keeps the FDA at a higher level throughout each frame. The trajectory of the moving item in A4 is the same as in A2, indicating that the two sequences are in fact similar. In these clips, the foreground item always travelled toward the centre of the screen at the same rate of pace. After going

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www.ijpast.in
Vol 12,Issue 3 .July 2022

forward for 22 frames, the object reversed course and started going backward. Figure 7 demonstrates that the PF tracker performed better in video sequence A4 (with occlusion) than in video sequence A2 (without occlusion) while attempting to track a moving object. The increasing occlusion in video sequence A4 enabled the PF tracker to disperse the particle across a larger region before the obstruction occurred, allowing for improved tracking. Thus, unlike in video sequence A2, the particle region is large enough to continue tracking the moving item even after the object has changed its traveling direction.

Work to be Done in the Future

Only single-predictor trackers, including Mean shift, Particle filter, and Kalman filter, are tested in this paper's tests. Many recent publications have suggested combining these trackers to improve tracking performance. Kalman filtering and Mean-shift tracking, for instance, have been fused by Li et al. [12], Zhao et al. [23], and Tang and Zhang [18]. Therefore, in the future, it will be necessary to conduct a series of experiments using this fusion tracker in order to determine their true performance. More complicated scenario simulation video sequences might be designed for future work and tested using the same trackers. The occlusion object might have the same color as the moving item or it could be larger to extend the occlusion period. Increasing the number of moving objects would help researchers evaluate the trackers' performance.

Conclusion

In this research, we created a series of synthetic videos to evaluate three widely used trackers by comparing their performance to that of the simulated videos. The Kalman filter, Particle filter, and Mean Shift tracker are all put to the test in these experiments. The effectiveness of each tracker was measured by its Sequence Frame Detection Accuracy. While most results corroborated the claims of earlier studies, PF tracker shockingly failed to identify objects whose movements were completely at random. In addition, using Frame Detection Accuracy, we explain in depth how occlusion impacts each tracking technique. When evaluating MS tracker's effectiveness, graphs. Ed is also used to compare the trackers' occlusion recovery abilities. When an occlusion does not occur, the MS tracker returns the best possible result. The greatest SFDAs for video sequences A1 (0.5196) and A2 (0.6071) are indicative of this. In video frame A3, complete occlusion caused the SFDA of the MS tracker to plummet to a meagre 0.0912. Full occlusion was also seen in frame 22 of video sequence A4. At frame 23, however, the moving item does a U-turn back to its position before complete occlusion, allowing the tracker to once again acquire it. The SFDA result of the MS tracker is marginally lower for partial occlusion than for the A1 and A2 video sequences without occlusion.

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