Multi-object Tracking in Aerial Image Sequences using Aerial Tracking Learning and Detection Algorithm

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ABSTRACT

Vison based tracking in aerial images has its own significance in the areas of both civil and defense applications. A novel algorithm called aerial tracking learning detection which works on the basis of the popular tracking learning detection algorithm to effectively track single and multiple objects in aerial images is proposed in this study. Tracking learning detection (TLD) considers both appearance and motion features for tracking. It can handle occlusion to certain extent, and can work well on long duration video sequences. However, when objects are tracked in aerial images taken from platforms like unmanned air vehicle, the problems of frequent pose change, scale and illumination variations arise adding to low resolution, noise and jitter introduced by motion of the camera. The proposed algorithm incorporates compensation for the camera movement, algorithmic modifications in combining appearance and motion cues for detection and tracking of multiple objects and enhancements in the form of inter object distance measure for improved performance of the tracker when there are many identical objects in proximity. This algorithm has been tested on a large number of aerial sequences including benchmark videos, TLD dataset and many classified unmanned air vehicle sequences and has shown better performance in comparison to TLD.

Keywords: Aerial images, tracking, learning, detection, minimum distance cue, object tracking

1. INTRODUCTION

Vision system has become an integral part of military applications, as in autonomous vehicles, where vision sensors are deployed for missions like surveillance, tracking etc. In particular, autonomous operation of unmanned air vehicles (UAVs) has progressively developed in recent years wherein, vision-based navigation, guidance and control has been the most focused research interest for trajectory tracking, path planning, obstacle avoidance, target localisation, target recognition, border and ground surveillance.

Although intelligence, surveillance, and reconnaissance missions still remain the predominant tasks of UAVs, their roles have expanded to diverse civilian, federal and commercial areas including law enforcement, environment monitoring, network connection and communication relay. The increased use of UAV in various complex missions has motivated the need to increase the autonomous capabilities of the vehicle. Hence, for future UAVs, computer vision forms an integral part of both advanced intelligent flight control techniques as well as autonomous vehicle mission planning.

Object tracking is a fundamental task in a wide range of military and civilian applications, namely surveillance, traffic monitoring and management, security and defense. In aerial imagery applications, the camera system is mounted on a moving aerial platform. As a consequence, the camera is not stabilised, and the acquired video sequences undergo a random global motion, that prevents the use of the object dynamics to predict the object location.

2. RELATED WORK

Object tracking involves following an object through a sequence of frames. The challenges involved in this include handling partial and complete occlusions of the object in some frames, multiple objects moving close to each other, crisscrossing each other etc.[1,2]. Tracking an object of interest by drawing inferences from the surrounding objects in motion is an area that needs to be researched upon. The main focus of the research is to develop a tracker that is robust enough to handle the scene adversaries and perform accurately in aerial image sequences.

Initial study showed the existence of three main techniques for object tracking, namely, point based, kernel based and silhouette based tracking[3]. A system for tracking moving objects in aerial images sequences taken from a moving camera consists of motion compensation module, motion detection followed by the tracking module. The basic tracking framework is given by Ali[4], *et al.,* where object of interest is tracked in UAV images using optimisation technique for blob tracking. However, today, learning based tracking by detection algorithms have become popular which combine detection and tracking in one framework.

Salti[5], *et al.*, evaluated a number of appearance adaptive trackers prominent among them being boost tracker[6], semi-boost tracker[7], beyond semi-boost tracker[8], incremental visual tracker (IVT)[9], MIL-boost tracker[10], track learn detect (TLD)[11] and STRUCK[12].

The authors propose a unified framework and evaluation

technique for the adaptive trackers and prove that learning based approach is superior to their non-learning counterparts. Out of all the successful trackers, STRUCK and TLD outperform others followed by IVT and MILBOOST in the cases of both partial and complete occlusions. After rigorous experimentation, we concluded that TLD works well on aerial images when compared to other algorithms. However, many failure cases were detected as will be explained in detail in the subsequent sections. Hence ATLD is towards improvising the TLD algorithm to suit target tracking in aerial image sequences.

3. TRACKING LEARNING DETECTION

Tracking learning detection is an algorithm[11,13] based on learning and can be used to track a chosen object of interest in a video stream. TLD method uses patches found on the trajectory of an optic-flow-based tracker to train an object detector. Updates are performed only if the discovered patch is similar to the initial patch. The output of the object detector is used only to reinitialize the optic-flow-based tracker in case of failure but is never used in order to update the classifier itself.

The tracker in TLD calculates the motion of the object between two consecutive frames assuming that frame-to-frame motion is limited and the object does not move out of the camera view. The initialisation is accomplished by manual intervention. An equally spaced set of points is formed in the bounding box. Optical flow of each of these points is calculated using Lucas - Kanade tracker[14]. Erroneous points are filtered out based on normalised cross correlation and forward-backward error measure. The tracker is likely to fail without recovering, if the object of interest moves out of the camera view.

Detector treats each frame independently, performs scanning of the entire image and localises all appearances that have been observed and learned in the past. It is a cascade of 3 stages. Only if a sub-window is accepted by one stage in the cascade, the next stage is evaluated. In the first stage, all sub-windows, that exhibit a variance lower than a threshold, are rejected. Second stage comprises of an ensemble classifier based on random ferns. The third stage consists of a template matching method that is based on the normalised correlation coefficient as a similarity measure.

Learning observes the errors of both tracker and detector, estimates detector's errors and generates positive and negative training examples to avoid these errors in the future. By the virtue of the learning, the detector generalises to more object appearances and discriminates against background. The Integrator combines the outputs of tracker and detector to give the final output. It also decides whether an output patch is good enough to be considered as a positive example for learning.

However, various challenges arise during object tracking in aerial images using TLD. Changes in pose, scale and illumination, partial and complete occlusion, similar objects moving close to each other, moving object coming to a halt, random jitter in image and noise are the major observations. These observations are tabulated in Table 1 along with the code level and algorithm level modifications as their solution.

4. ATLD – AERIAL - TLD FOR TRACKING OBJECTS IN AERIAL IMAGE SEQUENCES

Based on the above observations, the TLD algorithm is modified and enhanced so as to overcome the problems and is called ATLD. This learning based tracker is represented in Fig. 1.
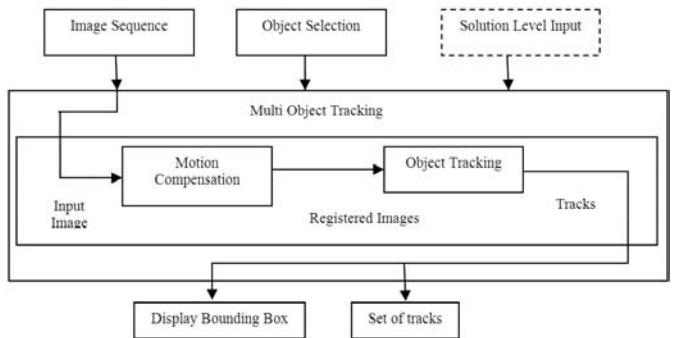
Figure 1. A learning based tracker.

4.1 Motion of the Camera

It is observed that TLD does not explicitly handle motion of the camera as the algorithm assumes that the appearance of the object doesn't change much. Aerial images taken from the camera mounted on platforms like UAV however introduce lot of noise, jitter and scale, pose and illumination changes. Therefore motion compensation module is incorporated as a pre-processing step to remove the effect of camera motion. Motion compensation is realised using image registration.

In ATLD, image registration is performed by considering a reference image and extracting the SIFT features[17]. The

Table 1. Problem area, modifications and extensions to tracking learning detection

Problem areas of TLD on aerial image sequences	Solution suggested	Implementation details	Handles
Motion of the camera introduces jitter and noise	Motion compensation	As a pre-processing module to the tracking module	Jitter, noise
Bounding box latching to occluder	Linear projection model	Introduced in the integrator	Partial/Complete occlusions, shadow, Criss-crossing of objects
Similar objects in the vicinity of the object of interest	Considering motion confidence along with detector confidence	Introduced in the integrator	Similar object in the vicinity, criss-crossing of objects
Only single object tracking	Extended to multi-object tracking	Using multithreads	Multiple object tracking
Accuracy in complex scenarios	Distance cue	Introduced as an algorithmic extension	Single object tracking in multi-object tracking environment

features thus detected are matched with the features detected in *n* subsequent images and a correspondence is established. The outliers are then filtered using RANSAC to find the correspondences that best fit a homography. Introducing motion compensation thus helped in mapping the images, and eliminating the problems of noise, scale and illumination changes.

4.2 Bounding Box Latching on to the Occluder

The motion compensated image sequence is tested for its capability of handling occlusions using TLD. Though TLD succeeded, there are frequent instances when the selected bounding box of the object of interest gets latched on to the occluder and remains there. This is because there is more than one output at the detector having similar confidence value.

As a solution to this, along with detector confidence, the motion confidence value is considered to decide on the final patch. A Kalman like linear projection model[15,16] is incorporated to remove the ambiguities when there are more than one detector outputs. Similarly, the tracker output is tested for appearance confidence before it is accepted as the final output which has improved the result of tracking and eventually the number of wrong patches learned is reduced considerably.

This also serves the purpose when the object selected goes out of frame for certain period of time and reappears; the tracker is able to track the object correctly. This is as a result of ATLD not restricting the search of the tracker to faraway objects.

4.3 Similar Objects in the Vicinity

The tracker is confused with neighbouring moving objects having similar detector confidence and motion confidence values as that of the object of interest. Under such circumstances too, the linear projection model helps in finding the right patch and the hence the tracking accuracy is greatly improved.

4.4 Multi-object Tracking

Tracking learning detection algorithm is basically designed to track a single object of interest. The ATLD is extended to multi-object tracking successfully using the concept of multithreading. Here the objects of interest are selected using a bounding box each and then the algorithm runs on each of these selected objects to give multiple tracks. The ATLD with this capability works well both for single object tracking as well as multi-object tracking. As expected, time complexity is affected. However, in order not to compromise on real time performance, we chose to track three moving objects in the scene successfully. Experiments have shown improved results on various aerial datasets. The test datasets included the proprietary UAV video sequences with different complexities like, camera motion, scale changes and illumination changes. ATLD algorithm is incorporated in the integrator part of the TLD framework.

4.5 Tracker Precision and Accuracy in Complex Scenarios

Analysis of the tracker and detector confidence values in the debug environment show that when there is no tracker output and the detector detects one or more qualified patch/s, the algorithm may chose the wrong patch as the target looking at the confidence value derived from appearance match. In such cases ATLD has the capability to choose the final match based on the distance measure which serves as an additional cue along with their appearance and motion confidence values. As depicted in Figs. 2 and 3, the algorithm measures the distance between the qualified patches of the object of interest and qualified patches of the other moving objects nearby, and maps the object of interest in frame (*n-1*) with the patch in frame *n* that has the minimum distance measure with Δ as the error. The detailed algorithm for tracking object of interest amongst other moving objects using ATLD is represented below.
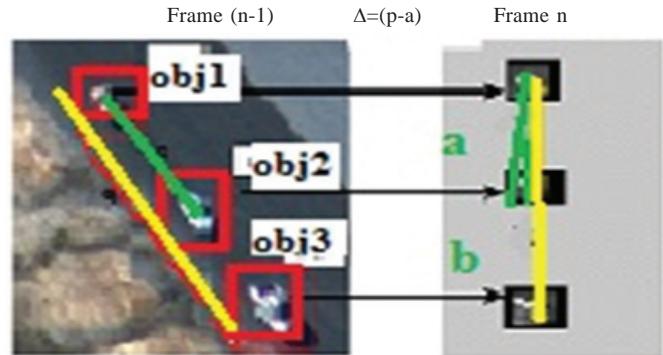
Figure 2. Minimum distance measure between the objects of frame *n* and (*n-1*).
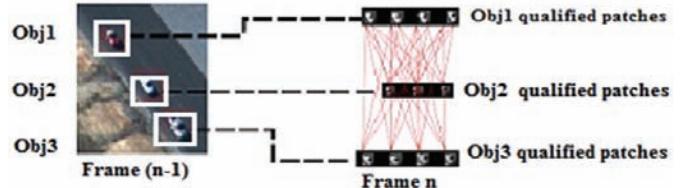
Figure 3. Distance cue between frame *n* and (*n-1*).

Algorithm: Aerial Tracking Learning and Detection

Input: Image Sequence
Output: Object tracks
Terminology: *bb* - bounding box, *dtconf* – detector confidence, *trconf* – tracker confidence, *tr* – tracker output, *dt* – detector output
1. Pre-process input images for camera motion.
2. For *n* moving objects (here *n=3*) in each frame
  a. If *tr*=1 and the trconf measure is sufficiently high
      Find all *dt* away from tracker && having higher confidence measure than trop
    If # of such *dt* == 1
     Get the motion confidence (*M*) of that *bb*
     If *M* is greater than a threshold
      Assign it to *op*
     End
    Else If # of such *dt* > 1
     Adjust *tr* ie, consider the *dt* around *tr* && find the mean of the *b* of these ops and give it as *op*.
    End

End
b. If (*tr=1*) and (*dt=0*)
   Output of the tracker is the required output
   End
c. If (*tr=0*)   /* No output from tracker*/
   i. Get all the patches which pass through fern classifier
   ii. Compute dtconf (*D*) for these clusters.
   iii. Compute *M* for all these patches
   iv. Retain those patches which have M greater than threshold.
   v. For all qualified patches of n moving objects
       Calculate the distance between qualified patches for the object of interest with all qualified patches of all other objects. Final Patch for the object of interest = Min ((distance between object of interest and other objects in frame (*n-1*)) - (distance between qualified patches of object of interest and other objects in frame (*n*)))
       End
   End
d. If *tr=0* and *dt=0* then
   Reinitialise the tracker
   End
3. Repeat steps 1 and 2 for subsequent images.
    This algorithm is verified and tested on different aerial sequences to establish the effectiveness of the same.

5.   RESULTS AND DISCUSSION

Experimental setup consisted of an environment to run original TLD as given by Kalal[13], *et al.,* and its enhancements in the form of ATLD. A debug environment is created to study the cause and effect of the algorithm on the input sequence. ATLD worked well and gave better results on the test datasets as supported by the quantitative analysis. The test datasets includes classified UAV video sequences, aerial sequences from UCF website (http://crcv.ucf.edu/data/UCF_Aerial_Action.php), benchmark sequences (http://i21www.ira.uka.de/image_sequences/), TLD dataset (http://personal.ee.surrey.ac.uk/Personal/Z.Kalal/dataset) and few in-house aerial sequences and a large number of classified data sequences. All simulations are carried out in MATLAB version R2013b with associated image processing toolkit on an i7 processor with processing capacity of 6 GB RAM and 500 GB hard disk.

5.1 Motion Compensation

Motion compensation module is incorporated as a pre-processing step to remove the effect of camera motion, thus eliminating noise in the form of jitter. Image registration using SIFT features extraction and matching[17] is performed to find the correspondences that best fit a homography. Figure 4 shows a sample result on an aerial image sequence.

Figure 4.   A panoramic image registered by UAV video image sequence.

5.2 Single Object Tracking Using TLD

The working of TLD algorithm on aerial image sequences is tested on the tabulated dataset. Though the algorithm performed well in simple cases, it failed in complex scenarios having the effects of illumination changes, occlusions or background clutter as aerial images are characterised by low resolution and noise. One such scenario where TLD failed due to presence of shadow is shown below. The same sequence, worked well using ATLD as implementing linear projection model along with motion confidence in the integrator helped in resolving the problem.

Figures 5(a) - 5(e) shows the tracking results using l TLD and Figs. 5(f) - 5(j) shows the tracking results of ATLD algorithm. Figures 5(c) and 5(d) shows failed tracker in frame 1368 and further fails in recovering as shown in frame 1465, However, ATLD accurately tracks the object of interest in all these frames.

5.3 Handling Illumination Changes

The other issue that is addressed in ATLD is that of sudden illumination changes. Here too, implementing linear projection model along with motion confidence in the detector, helped in resolving the problem. Output of UAV1 sequence is as shown in the frames Fig. 6. The object of interest in red color bounding box is track correctly using ATLD, though there was large illumination change in these frames.

5.4 Object Appearance and Disappearance

The case wherein the object of interest leaves the frame

Frame 1	Frame 310	Frame 1336	Frame 1368	Frame 1465

(a)	(b)	(c)	(d)	(e)
(f)	(g)	(h)	(i)	(j)

Figure 5.   Biker sequence.
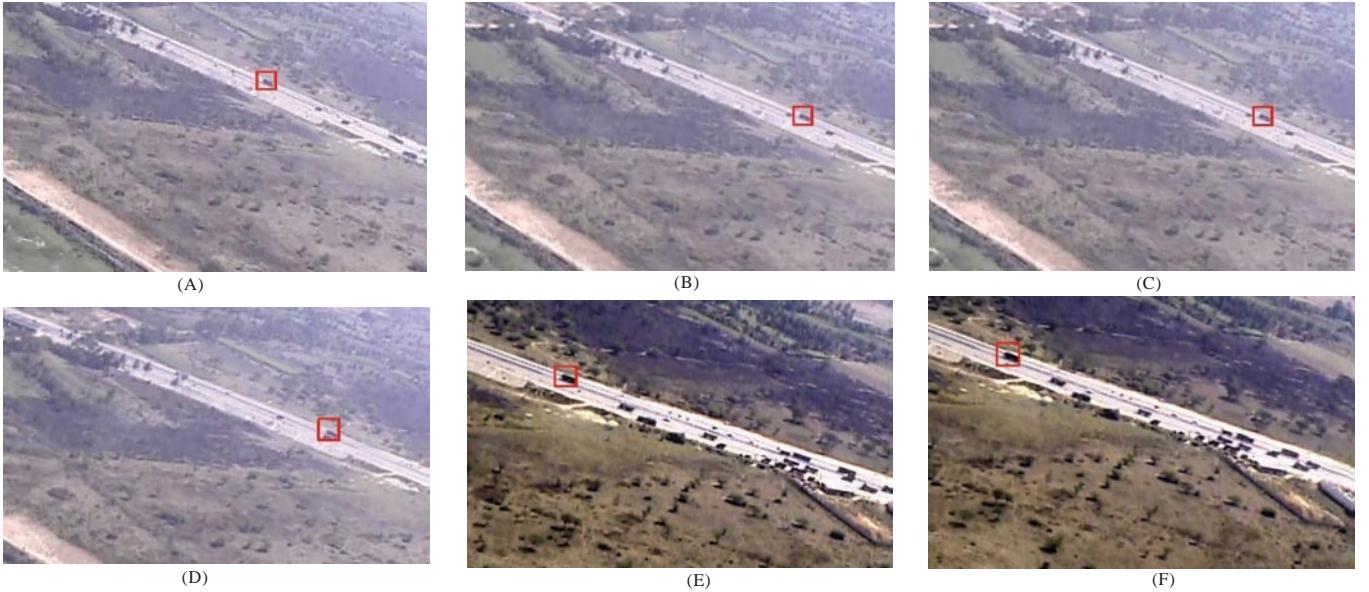
Figure 6. UAV1 sequence: Handling illumination changes.

and reappears in later frames is depicted in frames A-F. ATLD successfully tracks such objects, as the detector confidence is high for those objects which have been learnt and reappear at a later stage after disappearing from the scene.

Figure 7 show as the object is selected manually in A (Frame 70). The object disappears in B-D (frame 104, frame117, frame 143) The object reappears in frames E–F (frame 157, frame 186) and is tracked successfully.

5.5 Tracker Tracking Similar Object in the Vicinity

Appearance matching may fail, as the detector may not give a single high detector confidence value when there are similar objects in the vicinity of the object of interest. One such case is as shown below where the bounding box latches on to similar looking vehicle passing near the object of interest. In case of ATLD, this problem is overcome as along with detector

confidence, motion confidence is considered together with linear projection to give accurate results.

As shown in Fig. 8, the first row show the tracking results of TLD and the images in the second row show the tracking results of ATLD algorithm. First frame in both the rows show the bounding box around the same object selected for tracking. The third, fourth and fifth images in the first row show that TLD gives wrong track results in frame 27, frame 79, and frame 92, respectively whereas ATLD successfully tracks the object of interest.

5.6 Multi-target Tracking

ATLD on single object tracking is further extended to tracking multiple objects using multithread processing but with time complexity being affected. Realtime performance was not compromised with three moving objects being tracked

Figure 7. UAV1 sequence: Object appearance and disappearance.

Figure 8. Traffic sequence.

Figure 9. Snapshots of multi-object tracking in selected aerial datasets.

in the scene. Few results are depicted as shown in Fig. 9.

5.7 Tracking Object of Interest with Distance Cue from Surrounding Moving Objects

Experimentation with ATLD tracker shows that the algorithm failed in certain scenarios where the motion and appearance confidence values of two or more objects become similar. One such example is as shown below in Fig. 10. Additional cue however, can help in resolving the issue of similar confidence values. Here distance of the object of interest

(a)

(b)
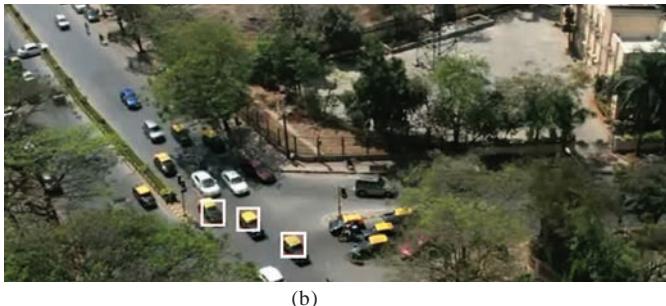
Figure 10. (a) Frame 24 – Tracking object of interest (middle taxi) failed and (b) Frame 24 - The object of interest is tracked accurately with distance measure cue.

and its surrounding moving objects is considered which brings in noticeable changes to the output as seen below.

5.8 Quantitative Analysis

ATLD thus shows satisfactory results on the different aerial datasets. Along with the relevant TLD dataset sequences, we tested the accuracy of the proposed algorithm on various proprietary UAV datasets which gave an insight to the working of TLD and ATLD that helped in bringing out comparisons between the two. All sequences were manually annotated and more than 60 per cent occlusion was annotated as 'non-visible'. The performance of the system is evaluated based on precision, recall and F-measure factors.

The precision-factor is a measure of the true positives (*tp*) of all the bounding boxes detected i.e. from all of true positives (*tp*) and false positives (*fp*) detected. It is given by Eqn. (1) as

$$precision-factor(P) = \sum \frac{tp}{tp+fp} \qquad (1)$$

The recall-factor on the other hand considers the false negatives (*fn*) or the missed bounding boxes as shown in Eqn. (2). Ideally, no true positive should be missed.

$$recall-factor(R) = \sum \frac{tp}{tp+fn} \qquad (2)$$

A perfect precision-factor of 1.0 means that the object of interest is detected correctly, but it doesn't say anything about whether all true positives were detected. Similarly, a perfect recall-factor of 1.0 means all true positives were detected, but doesn't say anything about how many remaining objects were classified incorrectly. F-measure gives the harmonic mean of the two.

$$F - measure = 2 * \frac{(P*R)}{(P+R)} \qquad (3)$$

Table 2 shows the performance measured using P/R/F-measure values. The results of ATLD outperformed original TLD in almost all the datasets chosen. Thus ATLD performs better in comparison with other benchmark learning based algorithms that have been compared by the authors of TLD. As observed, the biker sequence and car chase sequence show drastic improvement in their recall values using ATLD. This is because the algorithm successfully tracks the object of interest in presence of shadow, occlusion and reappearance of the object while TLD fails (the bounding box stuck to the occluder in case of occlusion).

Table 2.   Performance evaluation on aerial dataset measured using precision (P)/recall (R)/F-measure (F)

Sequence	Frames	TLD P/R/F	ATLD P/R/F
Biker[4]	1989	0.93/0.70/0.80	0.99/0.96/0.97
UAV1[4]	616	0.82/0.88/0.85	0.90/0.90/0.90
UAV 2[4]	1833	0.84/0.88/0.86	0.92/0.88/0.90
3 Car[2]	1301	0.83/0.84/0.84	0.90/0.89/0.89
Traffic 1[3]	156	**0.88/0.91/0.89**	0.88/0.91/0.89
Traffic 2[3]	227	0.82/0.80/0.81	0.85/0.90/0.87
Car[1]	945	0.91/0.95/0.94	0.99/0.99/0.99
Car Chase[1]	9928	0.87/0.77/0.78	0.96/0.98/0.97
Pedestrian 2[1]	338	0.89/0.90/0.89	0.93/0.95/0.94

Table 3 compares P/R/F values of tracking object of interest without taking distance cue from the surrounding moving objects and that with the distance cue on multi-object tracking ATLD platform. We restricted ourselves to tracking three objects because of the obvious reason of increased time complexity in multithreading environment.

As seen in the Table 3 on implementing target tracking using distance measure as cue from surrounding moving objects, the performance of the tracker improves considerably. The reason for the improved numbers in P/R/F values owe to the assumption that distance travelled by the objects is small in consecutive frames and all the nearby moving objects travel

Table 3.   Performance evaluation on aerial dataset measured using precision (P)/recall (R)/F-measure (F)

Sequence	Frames	Tracking without distance cue P/R/F	Tracking with distance cue P/R/F
UAV1	616	0.90/0.90/0.90	0.94/0.94/0.94
UAV 2	1833	0.92/0.88/0.90	0.96/0.99/0.97
3 Car	1301	0.90/0.89/0.89	0.99/0.99/0.99
Traffic 1	156	0.88/0.91/0.89	0.96/0.98/0.97
Traffic 2	227	0.85/0.90/0.87	0.97/0.97/0.97
Car Chase	9928	0.96/0.98/0.97	0.98/0.98/0.98
Pedestrian 2	338	0.93/0.95/0.94	1.00/1.00/1.00

in the same direction. However there are cases, especially the ones with severe occlusions (> 60 per cent) and the ones in which surrounding objects do not move in the same direction, the algorithm tend to fail and hence are further being researched upon.

6.   CONCLUSION

An enhancement to the popular TLD algorithm for aerial image sequences called aerial TLD is proposed. The various challenges that arise during object tracking in aerial image sequences like scale and illumination changes, partial and complete occlusion, similar objects moving close to each other, moving object coming to a halt, random jitter and noise have been taken care. Also TLD algorithm which basically is designed to track single objects is enhanced to track multiple objects.

Further, in the framework of multi-object tracking using ATLD, the object of interest is tracked successfully taking cues from the surrounding moving objects. Results demonstrate the improved accuracy when compared to the state-of-the-art. However, the present work utilises distance cues from the movement of neighboring objects in the scene under the assumption that inter object distance do not vary much and all the objects move in the same direction. So the future work will look into overcoming these limitations and also automatically selecting the neighbours in the scene.

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