Aircraft Tracking System Based on KLT Feature Tracker

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Abstract --- Tracking of aircraft in an image using the feature tracking algorithms faces significant challenges under conditions of severe aircraft rotation, highly cluttered background presence, arrival and collision with other aircrafts and sun, excessive noise, and varying lightening conditions due to weather changes. A robust and real-time framework has been provided in this paper for tracking aircraft in low resolution images using image modeling and feature tracking techniques. The main focus of the algorithm is on utilization of Kanade-Lucas-Tomasi (KLT) feature tracker and the manipulation of those features for modeling and tracking of the object (aircraft) in attention. The focus of object tracking is focused on both the feature tracking and image modeling by the manipulation of KLT features. The features of KLT algorithm are manipulated to extract only the features of the aircraft and an image model of the aircraft using histogram, mean, and standard deviation is created which is utilized in the consecutive frames to track movements and collisions. The algorithm has been tested on self-defined dataset of 18000 frames and the results are presented with high accuracy and efficiency.

Keywords—*Kanade-Lucas-Tomasi (KLT), Aircraft Tracking, Feature Tracking and Image Modeling*

I. INTRODUCTION

Radars are generally used for detecting and tracking aircrafts. However, radars are expensive and use active illumination of aircrafts with electromagnetic waves. This gives away the position of the radar which is undesirable from military point of view and is also a major source of interference with nearby electronic equipment. On the other hand, vision sensors are low cost, passive and robust to jamming. This motivates the use of vision-based aircraft tracking. Even though visual sensors have a limited range compared to radars, they can be used for a number of applications. Visual tracking can be used to guide aircrafts during their approach for landing and for automatic scoring of aerobatics performance. In the military, visual aircraft tracking can be used to aim and guide weapons. Motion estimation and tracking in videos is an established area of computer vision. Computer vision has been successfully used for tracking pedestrians and other objects of interest. Tracking algorithms can be roughly divided into optical flow and local feature-based techniques. Optical flow-based techniques exploit the fact that there is minimal change in images that are taken at small intervals of time, such as in video, even in the presence of relative motion between the camera and the objects in the scene. Optical flow-based techniques give a dense field of flow between frames. However, areas of the image which are not rich in texture (such as plain color) are a major source of error. A comparison of optical flow-based tracking techniques is given by Barron et al. [1].

Feature based tracking algorithms extract local features (regions) from the first frame and search for the corresponding features in the subsequent frames. Identifying features, that are good for tracking, is an important first step in these techniques. In some cases, the choice of features can be restricted to a pre-selected object which is required to be tracked such as aircrafts in the context of this paper. In such cases, the object of interest must be detected by an object detection algorithm such as a Haar-based detector [2].

Object detection algorithms search for the appearance of an object of interest in an image, usually at multiple scales. Compared to tracking, object detection takes more computational resources which is why tracking between frames is preferred as opposed to frame by frame detection. This paper proposes two modifications to the Lucas and Kanade [3] tracking algorithm which is based on optical flow estimation however, it has been extended by Shi and Tomasi [4] to include a feature identification step and cater for affine transformations of the features.

II. LITERATURE SURVEY

Trucco and Plakas [5] give a detailed survey of video tracking techniques and divide tracking into motion and matching problems. The former predicts the location of the tracked object in the next frame whereas the latter confirms the location of the tracked object in the next frame. Thus tracking proceeds by iterating between two stages namely predict (define a search region) and update (confirm the object location). In the simplest model, prediction may be a fixed window around the previous location. The size of the window is a trade-off between accuracy and speed. Small search regions may miss the tracked object in the next frame whereas a large search region requires more computational resources. This problem has been addressed by using multiresolution image pyramids and performing tracking in a coarse-to-fine manner [6].

The simple search window model (including the multiresolution image pyramid based) does not take advantage of the temporal motion information of the object. Using this information, the search region can be more accurately predicted. A well-known model that keeps an estimate of the dynamic state of a system to predict the search region for the next frame, is the Kalman Filter [7][8]. Extended versions of the Kalman Filter [7][9] have also been used to deal with non-linear dynamic systems.

Kalman Filter has also been used for estimating depth from image sequences. However, Kalman Filter is based on Gaussian distribution and therefore supports a single peak [5]. In other words, only one target can be tracked. Particle filtering allows multimodal distributions for simultaneous tracking of multiple targets [10]. Even if one target is of interest and needs to be tracked but in the presence of many others, it is sometimes better to track all of them in order to avoid losing the target of interest in the event of interference from others.

An interesting fact is that the Lucas and Kanade [11] algorithm was developed for solving the stereo correspondence problem which is analogous to video tracking in the sense that there is relative movement of the object (in the images) with respect to the camera. However, in stereo, this movement occurs in the frames because the two images are acquired from different viewing points. On the other hand, in video tracking either the object to be tracked or the camera or even both could be moving. Unlike stereo, video tracking can exploit the motion information which is not available in a static pair of stereo images. But again, if both the object and the video camera are moving (as is the case in this paper), it can result in quite complex motion models. The complexity of motion model further increases when there is significant variation in the depth (distance from camera) of the object and when the camera also performs optical zoom operations.

In this paper, we present a new framework that includes processes for handling all the issues present in the above mentioned system with increased efficiency and accuracy including the removal of noise, handling of the camera rotation issue in the KLT algorithm [8], change in the aircraft texture due to extensive rotations and low resolution of the image, and the presence of a highly cluttered and rapidly varying background.

III. PROPOSED ARCHITECTURE

The framework and algorithm proposed in this paper is based on Kanade-Lucas-Tomasi (KLT) features [4][12]. KLT feature tracker tracks the features from one frame to the next. The features are scattered throughout the image depending upon the overall texture of the background, and the number of objects in the image. The aircrafts are detected by correlating the matching features in consecutive frames, but KLT alone provides a low accuracy and prediction performances with majors errors in aircraft detection and a huge miss ratio in the presence of highly textured background with a large number of objects. For handling this complete problem, a framework and algorithm has been established, which is presented in this paper. The algorithm works as follows:

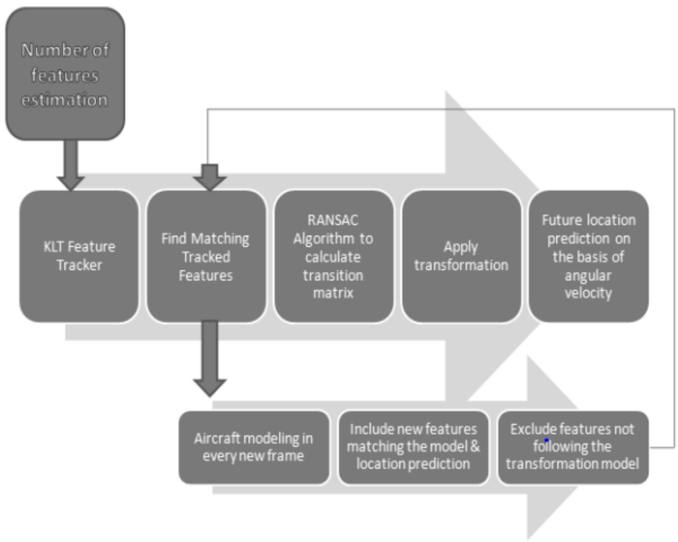

Figure 1:Algorithm framework

A. *Estimating number of features*

KLT feature tracker finds out 'n' number of features in the first image, and tracks these features in the upcoming images. If a feature is lost, an alternative feature is found which is tracked from their onwards. The number 'n' varies the effects on the efficiency and accuracy of the tracking and detection of objects. If the number 'n' is significantly high, the KLT algorithm consumes a lot of time and the efficiency of the algorithm is affected. Many weak features and image noise is also tracked if 'n' is very large. On the contrary, a small value of 'n' leaves behind many important and strong features affecting the accuracy of the detection and tracking to a large extent. We have tested the accuracy and efficiency of our algorithm by selecting different values of 'n' on 8 different videos of 640*360 to estimate the correct number of features to be tracked for best performance and results. The value present in the table below is given by the formula.

Efficiency E= (Time Consumed in feature tracking T/ Maximum Time Consumed M for varying 'n') + (Time consumed in algorithm T2/ Maximum time Consumed M2 for varying 'n').

Accuracy percentage is calculated by the number of correctly tracked features. where M is miss rate and C is the number of correctly tracked features.

V= (Efficiency percentage+ Accuracy percentage)/2

The average calculated values provided an estimate to select the value of 'n' between 100 and 150 features for best performance in terms of the efficiency and accuracy of code. The large number of features not only has a negative impact on the efficiency but also affect the accuracy by capturing a large number of features containing salt and pepper noise. The number of features ‘n’ should ideally be kept between 100 and 150 in the case of low resolution images with moderately textured aircrafts and backgrounds. These tests have been conducted on eight different videos of the same resolution, and the consistency in the trend is visible.

B. Including new features in the aircraft tracking

The aircrafts goes through massive rotations in its course of motion due to which almost every feature is lost at one time or another. Since, the previous features continue to lose, new features arrive, but there are certain standards that the new features should pass to be included in the aircraft tracking model for further computation. If a feature does not pass those standards, then it will not be included. This is done to ensure that the new features do not arrive due to background cluttering, noise, or some other issue. The standards that the new feature has to pass are explained in the flow chart below:

- Is within the range of the rectangular region tracking the aircraft
- Follow the same trajectory, translation, and velocity as the aircraft features
- Comply with the present dynamic model of the aircraft
- Is not a feature on the noise which is made sure by checking if a features stay for at least 30 frames.

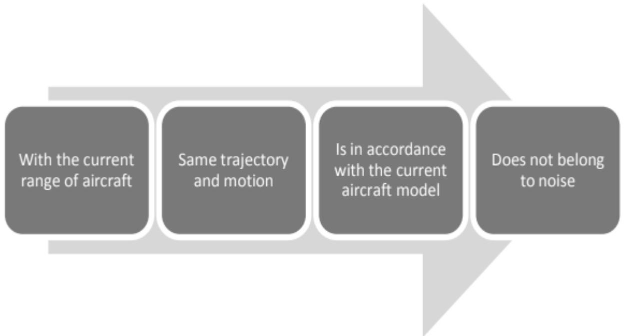

Figure 2: New features inclusion algorithm

If a new feature is in accordance with all these 4 standards, it is also included in the aircraft features to help in tracking in the upcoming frames. The features that stay in an image for less than 30 frames are considered as noise features and are not dealt with. The method of noise detection utilized in this application is much more efficient than the traditional techniques including median filter for noise removal.

IV. RESULT DISCUSSION

This section provides the results of the efficiency and accuracy of the algorithm, and comparison with other technique of aircraft tracking. A large dataset with over 18000 frames covering all challenging conditions is used. The hit ratio for tracking of aircraft features in the proposed framework is 92%.

Table 1: Aircraft tracking accuracy results

Hit Ratio 92%	Miss Ratio 8%
False Alarm (included features that do not belong to aircraft) 9.6%	Correct Rejection (Excluded features that belong to the aircraft) 1.1 %

The accuracy of the future location prediction of the aircraft after ‘n’ number of frames has been estimated for varying number of frame delay including 5, 10, 30, and 60 frames which accommodate for time intervals for 333ms to 2 seconds. The results of the accuracy of prediction are presented below:

Table 2: Aircraft prediction accuracy results

10 frames	20 frames	30 frames	60 frames
98.2%	96.4%	92.2%	85.1%

The noise reduction technique presented in the algorithm has shown an overall hit ratio for the removal of features tracked from noise to be around 83.32%. The hit ratio and miss ratio of the framework has been compared with Stavros et al [13] and Jeffrey et al [14]. Compared to the hit ratio between 80% and 85% of both above algorithm, the framework provided in this paper provides a hit ratio of 92%.

V. CONCLUSION

In this paper, we proposed a predictive technique for aircraft tracking and future location estimation based on KLT feature tracker, RANSAC algorithm, and image matching and modeling techniques. Based on the experimental dataset, the proposed work can achieve a tracking accuracy of 92% and prediction accuracy as high as 98.2%. The proposed work handles the challenges of extensive aircraft rotation, cluttered background environment, low resolution of images with high noise ratio, and collision of aircraft with other objects effectively.

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