



Robust Approach for Object Tracking Via Collaborative Observation Model: A Review

Neha K. Holey*, Vinod Nayyar
Dept. of Master of Engineering
(WCC) Nagpur, Maharashtra, India

Abstract— *Object tracking is performed using monitoring object's spatial and temporal changes during a video sequence. . Even though much progress has been made in recent years, it is still a challenging problem to develop a robust algorithm for complex and dynamic scenes due to large appearance changes caused by varying illumination, camera motion, occlusions, pose variation and shape deformation. While most existing algorithms are able to track objects well in controlled environments, they usually fail in the presence of significant variation of the object's appearance or surrounding illumination. In this paper a Robust approach for object tracking via Collaborative Observation model that integrates Pattern Classification method and Pixel-Based Change Detection method is discussed. And a detail survey of different object tracking methods available in the literature including analysis and comparative study of different techniques used for tracking is done.*

Key words— *Object detection, object tracking, background, foreground*

I. INTRODUCTION

Object tracking is an important task within the field of computer vision. The proliferation of high-powered computers, the availability of high quality and inexpensive video cameras, and the increasing need for automated video analysis has generated a great deal of interest in object tracking algorithms. There are three key steps in video analysis: detection of interesting moving objects, tracking of such objects from frame to frame, and analysis of object tracks to recognize their behavior. Object tracking has wide range of applications - some of which are surveillance, activity analysis, classification and recognition from motion and human-computer interfaces. The aim of object tracking and detection is to establish a correspondence between objects or object parts in consecutive frames and to extract temporal information about objects such as trajectory, posture, speed and direction. While much progress has been made in recent years, it is still a challenging problem to develop a robust algorithm for complex and dynamic scenes due to large appearance changes caused by varying illumination, camera motion, occlusions, pose variation and shape deformation[1].

The goal of object tracking is to estimate the states of a target object in an image sequence. An image, usually from a video sequence, is divided into two complimentary sets of pixels. The first set contains the pixels which correspond to foreground objects while the second and complimentary set contains the background pixels. This output or result is often represented as a binary image or as a mask. It is difficult to specify an absolute standard with respect to what should be identified as foreground and what should be marked as background because this definition is somewhat application specific. Generally, foreground objects are moving objects like people, boats and cars and everything else is background. Many times shadow is classified as foreground object which gives improper output [9].

The basic steps for tracking an object are object detection, object classification, object tracking. Object Detection is to identify objects of interest in the video sequence and to cluster pixels of these objects. In object classification, object can be classified as vehicles, birds, floating clouds, swaying tree and other moving objects. Object Tracking can be defined as the problem of approximating the path of an object in the image plane as it moves around a scene. The approaches to track the objects are point tracking, kernel tracking and silhouette [2].

II. LITERATURE SURVEY

There is a rich literature in object tracking and here we discuss the most related work.

Wei Zhong et al. [1] present a robust object tracking algorithm based on a sparse collaborative appearance model. Within the collaborative appearance model, author develops a sparse discriminative classifier (SDC) and sparse generative model (SGM) for object tracking.

In the SDC module, a classifier is used that separates the foreground object from the background based on holistic templates. The training image set is composed of positive templates and negative templates. The target object is represented by positive templates, background and images with part of target object are represented by negative templates. This facilitates better object localization as samples containing only partial appearance of the target are treated as the negative samples. So system effectively deals with cluttered and complex background.

In the SGM module, a histogram-based method is presented that takes local appearance information of patches and occlusions into consideration. In this module, overlapped sliding windows are used on the normalized images to

obtain collection of all patches and each patch is converted to a vector. Then the dictionary is generated with cluster centers of all the collected patches using the k-means algorithm and the sparse coefficient vector of each patch is normalized and concatenated to form a histogram. Histogram segments of occluded patches are not taken into account when computing the similarity between histograms of candidate and template histogram. SGM module effectively estimates and rejects the occluded patches to improve robustness.

Since the appearance of an object often changes significantly during the tracking process, the update scheme is important and necessary. An update scheme is developed in which the SDC and SGM modules are updated independently. For the SDC module, the negative templates every several frames from image regions away the current tracking result are updated. The positive templates remain the same in the tracking process. For the SGM module, the dictionary D is fixed during the tracking process. Therefore, the dictionary is not incorrectly updated due to tracking failures or occlusions. Thus the system effectively deals with appearance changes. However, this system is less effective in handling tracking drifts problem as in this system errors are likely to accumulate during update scheme and can cause tracking failure. And trackers based on holistic appearance model are less effective in handling drifts.

David A. Ross et al. [2] present an appearance based tracker that incrementally learns a low dimensional subspace representation of target object for robust object tracking while target undergoes pose, illumination, appearance changes. To estimate the locations of the target objects in consecutive frames, a sampling algorithm with likelihood estimates, which is in contrast to other tracking methods that usually solve complex optimization problems using gradient descent is used. Also, it continuously updates the model representation to reflect appearance variation of target. Although it has been shown to perform well when target objects undergo lighting and pose variation, this method is less effective in handling heavy occlusion or non-rigid distortion as a result of the adopted holistic appearance model.

S. Avidan et al. [3] present an ensemble tracker that provides pixel based binary classification to differentiate between target and background. Ensemble tracker maintains an implicit representation of foreground and background using classifiers. In this technique, ensemble tracker combines collection of weak classifier into single strong classifier using Adaboost to present better result than any of the weak classifier. The tracker constantly updates collection of weak classifier to separate the foreground and the strong classifier is used to label pixels in next frame. The strong classifier which is used to label pixels in the next frame as either belonging to the object or the background provides a confidence map. The peak of the map, and hence the new position of the object, is found using mean shift. Although this method is able to differentiate between target and background, the pixel-based representation is rather limited and thereby constrains its ability to handle heavy occlusion and clutter.

Adam et al. [4] propose a fragments-based method to handle occlusions. In this method, histograms are extracted for each template patch and then these histograms are compared with those extracted from multiple regions in target image. The template object is represented by multiple image fragments or patches. The patches are arbitrary and are not based on an object model. Every patch votes on the possible positions and scales of the object in the current frame, by comparing its histogram with the corresponding image patch histogram. It minimizes a robust statistic in order to combine the vote maps of the multiple patches. The target object is located by a voting map formed by comparing histograms of the candidate patches and the corresponding templates. However, the template is not updated and thus this approach is sensitive to large appearance variations.

Maheub Murshed et al. [5] present an Edge Segment based tracking algorithm that is used to identify moving objects in image sequence. In this algorithm, edge segment based on Canny edge map is used by utilizing the edge structure in the moving object region and curvature based features are used for moving edge registration. A Kalman filter based predictor is used for tracking each individual edge segments and edge segments are clustered by using weighted mean shift algorithm. Although this method is able to track moving object or part of it effectively under varying illumination and partial occlusion, it cannot deal with full occlusion.

Mei and Ling [6] present a visual tracking algorithm based on a generative sparse representation of templates. In this method, the target candidate is represented as a linear combination of the learned template set composed of both target templates and the trivial template which has only one nonzero element. The assumption is that good target candidate can be sparsely represented by both the target templates and the trivial templates. In this method ambiguities are likely to accumulate and cause tracking failure.

Liu et al. [7] propose an online robust and fast tracking algorithm using a two stage sparse optimization approach. This tracking method selects a sparse and discriminative set of features to improve efficiency and robustness. No shape or motion priors are required for this algorithm. Both the training set and the template library models are online updated. Two-stage sparse optimization is solved jointly by minimizing the target reconstruction error and maximizing the discriminative power by selecting a sparse set of features. As the number of discriminative features is fixed, this method is less effective for object tracking in dynamic and complex scenes.

In [8], J. Huang et al. propose an algorithm based on histograms of local sparse representation for object tracking where the target object is located via mode seeking (using the mean shift algorithm) of voting maps constructed by reconstruction errors. That is, this algorithm operates under the premise that the most likely target object location has minimal reconstruction error based on sparse representation. However, this method is less effective in differentiating the foreground patches from the background ones as a result of generative approaches based on sparse representation.

Table I Comparative analysis of different techniques for object tracking

No.	Techniques/ algorithm	Advantages	Limitations
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1.	Collaborative appearance model and update scheme [1]	Deals with cluttered and complex background and estimates and rejects possible occluded patches effectively.	Tracking drifts problem is not removed effectively.
2.	An incremental visual tracker (IVT) with adaptive appearance model	It can deal appearance changes well.	Less effective in handling heavy occlusion and occasionally drifts from target object.
3.	Ensemble tracker	Low computational cost	Tracker cannot handle heavy occlusion.
4.	Edge Segment based tracking algorithm	Can track moving object or part of it effectively under varying illumination and partial occlusion.	Tracker cannot handle full occlusion.
5.	Fragment-based tracker	Remove partial occlusion with a representation based on histograms of local patches.	It cannot handle appearance changes.

III. PROPOSED APPROACH

Collaborative Observation model that integrates Pattern Classification method and Pixel-Based Change Detection method is a robust approach for object tracking for drastic appearance changes and to overcome the tracking drifts problem.

A. Pixel-Based Change Detection method

Pixel-wise Fuzzy XOR Operator is used for change detection. In this method, the binary XOR operation is taken as a benchmark. Its fuzzy version is used for change detection. Our rationale here is as follows. Assume that we have two binary images (composed of only ones and zeros) and we want to detect the changed pixels in these.. The change detection is done by XOR-ing the two binary images pixel-wise. This operation gives '0' for pixels having same value in both images, and gives '1' for pixels having different values. And detected changes will be foreground image.

B. Pattern Classification-based Adaptive Background Update Method

With the acquisition of an image, the first step is to distinguish objects of interest from the background. In surveillance applications, those objects of interest are usually humans. Their various shapes and different motions, including walking, jumping, bending down, and so forth, represent significant challenges in the extraction of foreground pixels from the image. Pattern Classification-based Adaptive Background Update Method is used to retrieve the background from a noisy video stream. In this method all moving objects are eliminated and provide updated background.

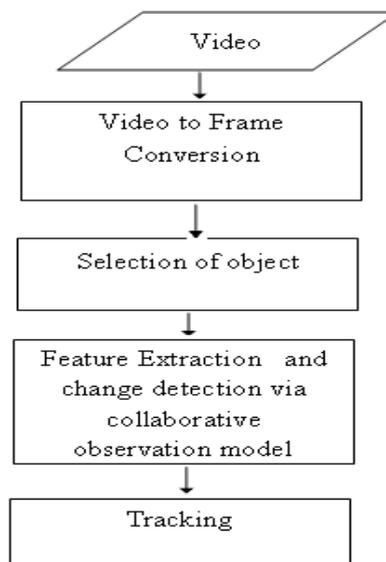


Fig. 1 .Flow of proposed approach

IV. OBJECTIVES OF THE PRESENT WORK

The objectives of the proposed approach are best described as below:

1. To estimate the states of target object in an image sequence.
2. To estimate and remove occlusion.
3. To alleviate the tracking drift problem effectively.
4. To develop a method that will effectively deal with cluttered and complex background.
5. To develop a robust object tracking method that will effectively deal with drastic appearance changes.

V. CONCLUSION

A brief survey of different object tracking methods available in the literature including analysis and comparative study of different techniques used for tracking is done. To improve the robustness and to overcome the tracking drifts problem a robust approach for object tracking via Collaborative Observation model is discussed.

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