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COMPARING DIFFERENT APPROACHES TOWARDS OBJECT DETECTION AND TRACKING

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Abstract: Object detection in a sequence is the first step in making a efficient surveillance system. Here we have taken into consideration various approaches different authors have taken into consideration for detecting the objects and further tracking them in a video sequence. Paper proceeds with basics of object detection and various techniques to do the same and as well as different algorithms for object tracking. Particularly we are comparing Particle filter and Kalman filter for object detection and tracking. Results of various authors are mentioned in the paper.

Key Words: Object Tracking; kalman filter; Particle Filter

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INTRODUCTION

Object detection [1] plays a vital role in any kind of image and video processing applications. Most importantly detection of interested objects is of prime importance. After detection next important concept is to track those detected objects using an estimator. For that feature selection plays an important role. Feature is the best thing for object representation. Various tracking algorithm use combination of color, edges, optical flow and texture detection for these processes. Feature selection is divided into filter and wrapper methods[2]. The filter methods selects the features based on a general criteria, for example, the features should be uncorrelated. The wrapper methods select the features based on the usefulness of the features in a specific problem domain, for example, the classification performance using a subset of features. In tracking two problems are associated: prediction and correction. Predict problem deals with predicting the location of an object being tracked in the next frame, that is identify a region in which probability of finding the object is high whereas correction problem deals with identifying the object in the next frame within designated region. A well known solution for prediction is Kalman filter[3][18], a recursive estimator of state of a dynamic system. To predict search region more effectively, mean shift is combined with kalman filter. In many of the tracking algorithm, the tracking performance depends up on the target image representation.

2. Detection Methodologies

Following diagram shows various approaches towards Object Detection.

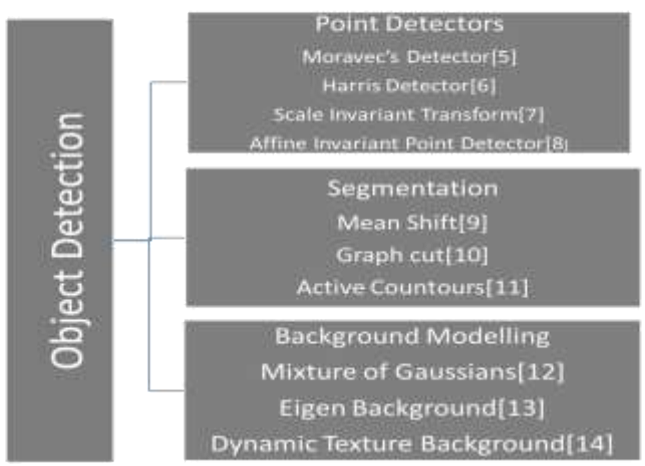

Fig 1

Point detectors[4][5][6] are used to find interest points in images which have an expressive texture in their respective localities. Interest points have been long used in the context of motion, stereo, and tracking problems. Interest point detectors include Moravec interest operator, Harris interest point detector and SIFT detector. Object detection can be achieved by building a representation of the scene called the background model[7][8][9] or the reference frame and after that comparing each coming frame with this reference frame and find any deviations from the reference frame. Any changes in an image region from the reference frame depicts a moving object. The pixels constituting the regions undergoing change are marked for further processing. This process is referred to as the background subtraction. Segmentation [10][11][12] partitions the image into perceptually similar regions. Segmentation describes, the criteria for a good partition and the method for achieving efficient partitioning. In mean shift clustering clusters are found in the spatial and colorspace. Here the process starts with an image with a large number of hypothesized cluster centers randomly chosen from the data. Then, each cluster center is moved to the mean of the data lying inside the multidimensional ellipsoid centered on the cluster center. The vector defined by the old and the new cluster centers is called the mean-shift vector. The mean-shift vector is computed iteratively until the cluster centers do not change their positions. Segmentation using graph cut can be described as graph partitioning problem, where the vertices (pixels) of a graph (image) are partitioned into N disjoint subgraphs (regions) by pruning the weighted edges of the graph. The total weight of the pruned edges between two subgraphs is called a cut. The weight is typically computed by color, brightness, or texture similarity between the nodes.

3. Methodologies for Tracking

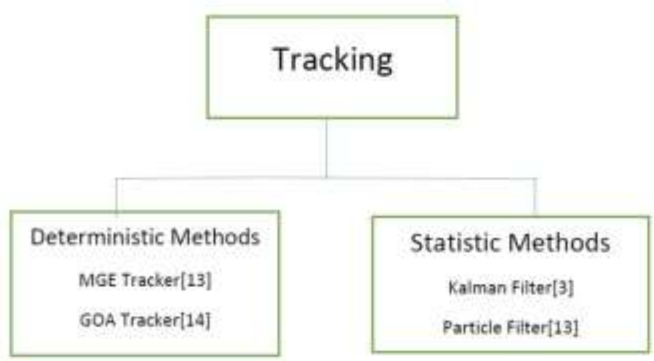

Fig 2

Object tracking tries to generate the trajectory of an object over time by locating its position in every frame of the video. Object tracker may also provide the complete region in the image that is occupied by the object at every time instant. The tasks of detecting the object and establishing correspondence between the object instances across frames can either be performed separately or jointly. Object location in every frame is found by means of an object detection algorithm, and then the tracker corresponds objects across frames.Deterministic method define a cost of associating each object in frame t − 1 to a single object in frame t using a set of motion constraints. Minimization of the correspondence cost is formulated as a combinatorial optimization problem. The correspondence cost is usually defined by using a combination of the following constraints.

--It is assumed location of object would not change.

--Small change in speed does not change drastically.

[13] handle these problems by first establishing correspondence for the detected points and then extending the tracking of the missing objects by adding a number of hypothetical points. [14] extend the above work by introducing the common motion constraint for correspondence. The common motion constraint provides a strong constraint for coherent tracking of points that lie on the same object; however, it is not suitable for points lying on isolated objects moving in different directions Measurements obtained from video sequence is associated with lot of noise. Also the object moving direction can have random motion, for example a vehicle moving in zigzag manner. Statistical methods solve these tracking problems by taking the measurement and the model uncertainties into consideration. Here we are going to see and compare two statistical method of detection and tracking

--Kalman Filter

--Particle Filter

3.1Kalman Filter

A Kalman filter is an optimal estimator. It infers parameters of interest from indirect, inaccurate and uncertain observations. It is recursive in nature so that new measurements can be processed as they arrive. Main features of Kalman filter in terms of tracking are

•Tracking can be achieved even if the objects goes out of the searched region.

•It takes into consideration lighting and occlusion effect of the target.

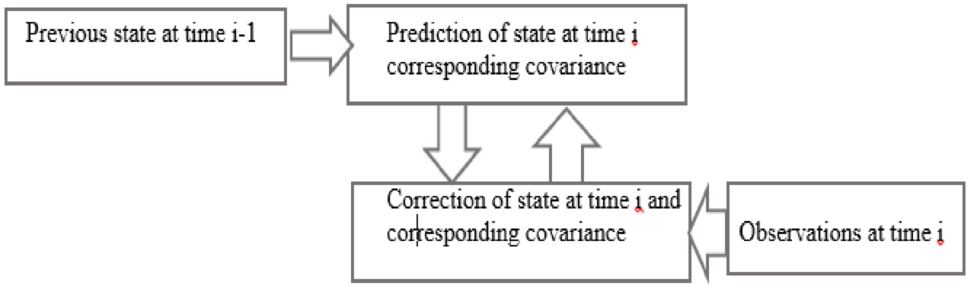

Fig 3: Flow for Kalman Filter

If all noise is Gaussian, the Kalman filter minimises the mean square error of the estimated parameters. The Kalman filter estimates a process by using a form of feedback control which means the filter estimates the process state at some time and then obtains feedback in the form of (noisy) measurements. The equations fall into two groups: time update equations and measurement update equations.

The time update equations point towards the current state estimate and error covariance prediction is used to obtain the main estimates for the next time step. Then measurement update step is responsible for the feedback by calculating the kalman gain. The time update equations is associated with prediction, while the measurement update equations is associated with correction equations.

In the case of kalman filters each iteration begins with predicting the process�s state using a linear dynamics model.

State Space Prediction:

For each time step T, a Kalman filter first makes a prediction *Xt* and it is given by

$X_t = AX_{t-1} + Bu_t$

X_{k-1} is process state at time t-1, A is process transition matrix

and B is control vector. Ut which converts control vector into state space

Error Covariance Prediction: The Kalman filter concludes the time update steps by estimating the error covariance forward by one time step

$P_t = AP_{t-1}A^T + Q$

P_{t-1} is a matrix representing error covariance in the state prediction at time t-1and Q is the process noise covariance. Lower the value of prediction error covariance Pt we can trust more on prediction of the state Xt . If the process is precisely modeled, then the prediction error covariance will be low.

3.1.2 Measurement Update

By using the time update step kalman filter will predict the state xt -1 and find the error covariance at time k. then after during the measurement update steps kalman filter uses measurements to correct its prediction

A). Kalman Gain

Kalman filter computes a Kalman gain K_t, which is used for correcting the state estimate xt

$K_k = P_k H^T (H P_k H^T + R_k)\hat{} - 1$

Where H is a matrix used for converting into measurement space from state space and R is measurement noise covariance.

B). State Update: Using Kalman gain $K_t$and measurements Z_t from time step t, where we can update the state estimate: $X_t = X_{t-1} + X_t(Z_t - HX_{t-1})$

C). Error Covariance Update: The final step of the Kalman filter�s iteration is to update the error covariance Pt. $P_t = (1 - K_t H) P_{t-1}$

If the measurements are accurate then the updated error covariance will be decreased.

4. Paticle Filter

Here to start of with particle filter. Its state space and dynamics need to defined[]. Firstly the window centre of the object is initialized that is $X = (x, y)$. Let the motion which is going to be estimated is Vt. $X_{t+1} = X_t + V_t + \mu_t$

Where μ is state prediction error.

Observation LikelihoodIt goes ahead with assumption that intensity Z_t^{int}, motion $Z_t^{mot}$and detector Z_t^{det}measurement are independent. Therefore it results in following likelihood.

$P(Z_t|X_t) = P(Z_t^{int}|X_t)P(Z_t^{det}|X_t)P(Z_T^{mot}|X_t)^{O_{t-1}}$[2]

When the object is occluded the motion continuity cannot be done by likelihood equation. Likelihood term comes from[19]. Combining detection and tracking for small sized object and integrating it into a adaptive filter. It made the roles of detector as Strong detector and weak detector. Strong one to detect the tracker and weak one to enhance the tracker. Future scope was to work on bigger sized object and do multiple object tracking.

5. Experimental Results from authors

After performing a series of experiments tracking of object in video was demonstrated.

Fig 4:Tracking using Kalman Filter

Fig 5: Tracking varied shape object

Fig6: Object detection using particle filter

6.CONCLUSION

The goal of this paper was to give a brief of various approaches and theory that is followed while anything about object detection in image as well as video processing is concerned. Different techniques for detection were studied and was found that background modelling gives better detection of the object. Also for tracking kalman filter and particle filter were studied. From observation of authors it can be concluded that Kalman filter is beneficial for surveillance in low populated areas and particle filter would be for more complex situation..

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