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Comparison of Multiface Tracking using Particle Filter and Kalman Filter

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Abstract— The primary objective of multi-face tracking is to detect and track multiple faces in the current frame in the video sequence under various environmental conditions. Tracking of the face movement in the input frame of the video is the key process for various real time applications such as video-conferencing, human robotics or human computer interface or in the analysis of social interaction. The important step is to determine the path of the face. The various techniques to track the multiple moving faces in an input frame of video have been proposed. This paper gives a brief analysis of recent long-term online multi-face tracking algorithms based on Particle Filtering and Kalman filtering

Index Terms— multi-face tracking; long-term multiface tracking; PF (Particle filter); KF (Kalman filter)

I. INTRODUCTION

The moving object tracking in video sequences has gained a great deal of interest in computer vision. Detection of moving objects in video streams is the first relevant step of information extraction in many computer vision applications, including traffic monitoring, automated remote video surveillance and people tracking. Conventional approach to object tracking is based on the difference between the current image and the background image. However, algorithms based on the difference image cannot simultaneously detect still objects. Furthermore, they cannot be applied to the case of a moving camera. Algorithms including the camera motion information have been proposed previously, but, they still contain problems in separating the information from the background. Object tracking has significance in real time environment because it enables several important applications such as security and surveillance to recognize people, to provide better sense of security.

Face detection is a computer technology that identifies human faces in digital images. It detects human faces which might then be used for recognizing a particular face. Face detection is acquiring the interest of marketers. Face detection and recognition are challenging tasks due to variation in illumination, variability in scale, locate, orientation and pose. Facial expression, occlusion and lighting conditions also change the overall appearance of face. Face tracking is different from face detection, face tracking uses temporal correlation to locate human faces in a video sequence, instead of detecting them in each frame independently. With temporal information, we can narrow down the search range significantly and thus make real-time tracking possible.

II. LITERATURE SURVEY

Initially face-detection algorithms were concentrated on the detection of frontal human faces, however latest algorithms effort to solve the more common and difficult problem of multi-view face detection. That is, the recognition of faces that are either rotated along the axis from the face to the observer (in-plane rotation), or rotated beside the vertical or left-right axis (out-of-plane rotation), or both. The latest algorithms take into relative changes in the image or video by factors such as face appearance, lighting, and pose. Face detection using artificial neural networks was done by Rowley [5]. It is robust but computationally complex as the whole image has to be scanned at different scales and orientations. Feature-based (eyes, nose, and mouth) face detection is done by Yow *et al.* [6]. Statistical model of mutual distance between facial features are used to locate face in the image. Markov Random Fields have been used to model the spatial distribution of the grey level intensities of face images. Some of the eye location technique use infrared lighting to detect eye pupil. Eye location using genetic algorithm has been proposed by Wechsler [3]. Skin color is used extensively to segment the image, and localize the search for face. The detection of face using skin color fails when the source of lighting is not natural.

Recently there have been a lot of research efforts in face tracking. Yang and Waibel [8] built a real-time face tracking system based on normalized color. Bradski [4] proposed the continuously adaptive mean shift algorithm. Colmenarez, et al. [7], DeCarlo and Metaxas [9] used a 3D face model in the tracking process. Malsburg [10] tracked specific feature points on the face to track the face. However, none of these algorithms deal with multiple faces, especially occlusion between faces, effectively. In this paper, we compare the multiple face tracking algorithms based on Particle Filter and Kalman Filter.

Images containing faces are important to intelligent vision-based human computer interaction, and research struggles in face handling include face recognition, face tracking, pose estimation, and expression recognition, etc. However, many described approaches imagine that the faces in an image or an image sequence have been recognized and limited. To figure fully automated systems that examine the information enclosed in face images, robust and efficient face detection algorithms are necessary. Given an image, the objective of face detection is to recognize all image sections which comprise a face regardless of its three-dimensional location, positioning, and lighting situations. Such a problem is rebellious because faces are not harsh and have a high degree of irregularity in size, shape, color, and texture. Target tracking has a number of appliances such as human computer interface, security, Surveillance and video conferencing [1]. The human face attitudes even more problems than other matters since the human face is a vibrant object that comes in many shapes and colors. However, facial detection and tracking delivers many gains. Facial recognition is not achievable if the face is not inaccessible from the background. Human Computer Interaction (HCI) could greatly be enhanced by using reaction, pose, and signal recognition, all of which need face and facial feature detection and tracking. While many different algorithms occur to accomplish face detection, each has its own faults and powers. Some practice flesh tones, some use forms, and other are even more complex concerning templates, neural networks, or filters. These algorithms experience from the same problem; they are computationally pricey. An image is only a group of color and/or light intensity ideals. Observing these pixels for face detection is time utilizing and difficult to achieve because of the wide dissimilarities of shape and pigmentation within a human face. Pixels often need reanalysis for scaling and precision, Haar Classifiers, to quickly sense any object, containing human faces, using AdaBoost classifier cascades that are centered on Haar-like features and not pixels.

III. MULTIFACE TRACKING

Face tracking generally involves two stages:

1) Face Detection, where a photo is searched to find any face (shown here as a green rectangle), then image processing cleans up the facial image for easier recognition.
2) Face Tracking, where which detected and processed face.

A. BAYESIAN FILTER

A Bayes filter [2] is an algorithm consumed in computer science for computing the probabilities of multiple beliefs to permit a robot to gather its location and direction Basically, Bayes filters approve robots to always update their most likely location within a coordinate system, based on the most recently acquired sensor data. This is a recursive algorithm. It comprises of two parts: prediction and innovation. If the variables are straight and normally scattered the Bayes filter becomes equal to the Kalman filter. In a simple example, a robot traveling throughout a grid may have several different sensors that provide it with information about its surroundings. The robot may lead out with inevitability that it farther from its original position, the robot has always less certainty about its position; using a Bayes filter, a probability can be assigned to the robot's belief about its current position, and that probability can be continuously updated from additional sensor information.

B. TRACKING USING PARTICLE FILTER

The particle filter which is used for multiface tracking is having several advantages and is as follows:

- No restrictions in model – can be applied to non-Gaussian models, hierarchical models etc.
- Global approximation.
- Approaches the exact solution, when the number of samples goes to infinity.
- In its basic form, very easy to implement.
  Superset of other filtering methods – Kalman filter is a Rao-Blackwellized particle filter with one particle.

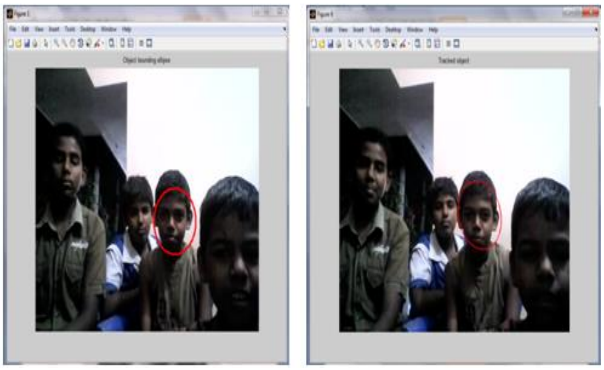

Fig -1: Tracking result of the input video using Particle Filter.

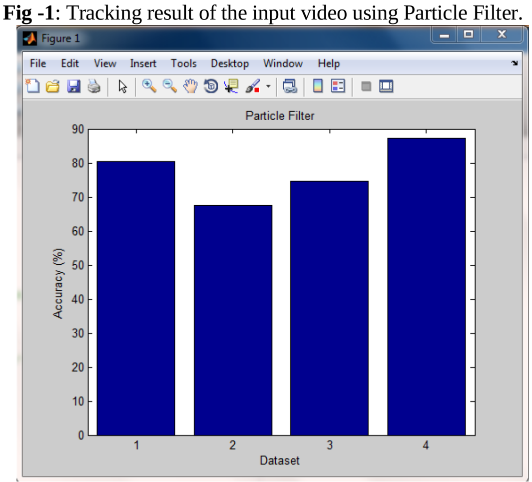

Fig -2: Performance Evaluation Graph of Particle Filter

IV.TRACKING USING KALMAN FILTER

Although they have advantages, there are many disadvantages for the existing particle filters and are as follows:

- Computational requirements much higher than of the Kalman filters.
- Problems with nearly noise-free models, especially with accurate dynamic models.
- Very hard to find programming errors (i.e., to debug).
- The most efficient number of particles cannot be calculated.
- High computational complexity
- It is difficult to determine optimal number of particles
- Number of particles increase with increasing model dimension
- Potential problems: degeneracy and loss of diversity

- The choice of importance density is crucial

The Kalman filter permits one to adjust a model of some physical process. The purpose is to determine the parameters of an a priori model. The algorithm of the Kalman filter has several advantages. This is a statistical technique that adequately describes the random structure of experimental measurements. This filter is able to take into account quantities that are partially or completely neglected in other techniques (such as the variance of the initial estimate of the state and the variance of the model error). It provides information about the quality of the estimation by providing, in addition to the best estimate, the variance of the estimation error. The Kalman filter is well suited to the online digital processing. Its recursive structure allows its real-time execution without storing observations or past estimates. The main advantage of the Kalman filter is its ability to provide the quality of the estimate (i.e., the variance), and its relatively low complexity.

The Kalman filter is essentially a set of mathematical equations that implement a predictor-corrector type estimator that is optimal in the sense that it minimizes the estimated error covariance—when some presumed conditions are met. Since the time of its introduction, the Kalman filter has been the subject of extensive research and application, particularly in the area of autonomous or assisted navigation. This is likely due in large part to advances in digital computing that made the use of the filter practical, but also to the relative simplicity and robust nature of the filter itself. Rarely do the conditions necessary for optimality actually exist, and yet the filter apparently works well for many applications in spite of this situation. This section describes the filter in its original formulation where the measurements occur and the state is estimated at discrete points in time.

Fig -3: Detection and Tracking Results of Kalman Filter: (a) Frame No.99 (b) Frame No.152 (c) Frame No.174 (d) Frame No.200 (e) Frame No. 247(f) Frame No. 288(g) Frame No. 306(h) Frame No.352 (i) Frame No.398

Fig -3 (a) illustrates the automatic face detection of the three faces which can be seen in the video. Since the two faces are close together it is taken as single track and the detected tracks 1 & 2 has to be kept tracking on. A yellow rectangle is used to show the track which is selected for the time being. Fig -3 (b) shows the 152nd frame of the input video. In this we can see two tracks which contain three faces. Since the two faces appear too close it is taken as a single track. Whenever distances between these faces occurs this track will get separated as two. In Fig -3 (e) the 247th frame of the video is shown, the 1st track seen here changes his face position as compared to the previous frame.

In Fig -3 (f) the 288th frame of the video is shown and here it can be observed that the position of one of the boys under 2nd track is changing. As soon as the face gets disappeared the track has to be deleted. It can be seen that the size of the 2nd track is minimized as compared to the previous frames and now it contains only one single face. In Fig- 3 (h) the face of the second boy in 2nd frame is deleted and the face of the other boy which was missing in the previous frame is created again. In Fig -3 (i) the 1st track gets deleted and the lost track of the previous frame is created again.

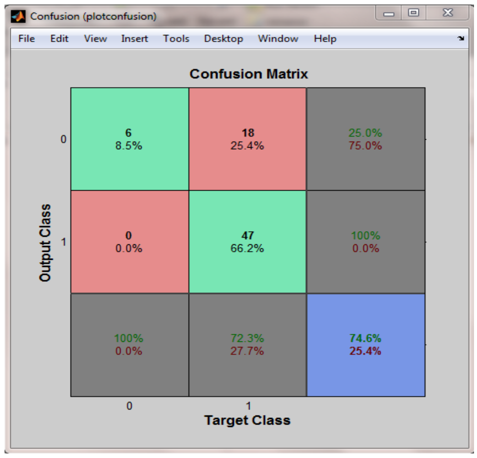

Fig -4: Confusion Matrix

700 running frames from the input video are taken for the evaluation. From the 700 running frames, 71 frames are taken in the sequence of 0, 10, 20…, 700. From these 71 frames those frames which are having multiple faces are given the value '1' and those which do not have faces are given the value '0'. To evaluate the accuracy of the method, allot the value '1' to those frames in which the multiple faces have been tracked and value '0' to the frames for the multiple face tracking failure.

In the confusion matrix shown in the Fig -4, X-axis shows the target class – the presence and absence of multiple faces and Y-axis shows the output class – correct tracking and incorrect tracking of the multiple faces in the input video. The (0, 0) box shows 6 frames among the 71 frames having no faces are correctly detected as non-faces and the corresponding accuracy is calculated. ie.,

$$\frac{6}{71} \times 100 = 84.5 \approx 85\%$$

The (0, 1) box shows no frames among the 71 frames having no faces incorrectly detected as faces. The (1, 1) box shows 47 frames among the 71 frames having faces that are correctly detected as faces and the corresponding accuracy is calculated. ie.,

$$\frac{47}{71} \times 100 = 66.2\%$$

The (1, 0) box shows 18 frames among the 71 frames having faces incorrectly detected as non-faces and the corresponding accuracy is calculated. ie.,

$$\frac{18}{71} \times 100 = 25.4\%$$

V. COMPARISON

For the evaluation of the performance of the system four different datasets with different time duration are taken and tested with both Particle filter and Kalman filter and the number of correctly tracked multiple faces is found more with Kalman filter compared to Particle filter.

TABLE-**1**: Accuracy Comparison between Particle Filter and Kalman Filter.

METHOD I *Tracking : Particle Filter*		**METHOD II** *Tracking : Kalman Filter*	
Data set	Accuracy	Data set	Accuracy
1	80.3	1	94.4
2	67.6	2	69
3	74.6	3	78.9
4	87.3	4	88.7

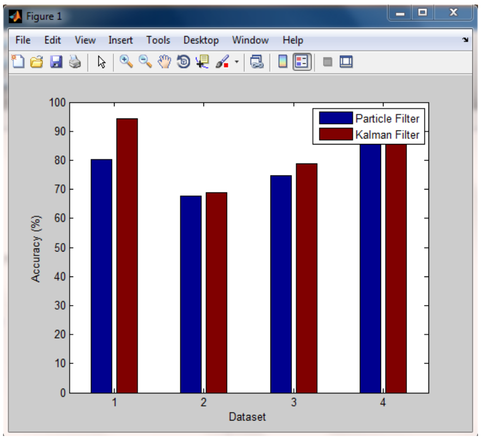

Fig -5: Accuracy Plot of Particle Filter and Kalman Filter

The performance evaluation graph obtained by comparing the results obtained from Particle filter and Kalman filter is given above.

VI. CONCLUSION

In many visual multi-objects tracking applications, the question when to add or remove a target is not trivial due to, for example, and erroneous outputs of object detectors or observation models that cannot describe the full variability of the objects to track. This decision process is difficult due to object detector deficiencies or observation models that are insufficient to describe the full variability of tracked objects and deliver reliable likelihood (tracking) information. The proposed algorithm addresses the track management issue and presents a real-time online multiface tracking algorithm that effectively deals with the above difficulties. An on-line multi-face tracking algorithm that effectively deals with situations where detections are rare or uncertain is presented. To achieve this, long-term observations from the image and the tracker itself are collected and processed in a principled way using two separate HMMs, deciding on when to add and remove a target to the tracker.

We can present a real-time, online multi-face tracking algorithm that effectively deals with missing or uncertain detections in a principled way. Tracking is formulated in a multi-face kalman filter framework. The size, top-left coordinate and velocity of motion of the detected face being the parameters of the Kalman vector; the predicted values are used to locate faces in the next frame. Faces are redetected and the templates are updated at discrete time intervals when the similarity measures, between the faces detected and respective face templates, are less than a preset threshold.

This method is applied on real-time videos and shows a significant performance increase, compared to a traditional approach relying on head detection and likelihood models only.

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