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Improved Particle Filter Approach for Multiple Object Tracking in Crowd Environment

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Abstract- Object tracking in video processing is a significance task because of its applications in surveillance, activity monitoring and recognition, traffic management etc. In outdoor and indoor environment multiple objects tracking is a challenging task because of poor lighting conditions, variation in poses, orientations, changes in location, shape and size etc. This paper proposes a method for tracking multiple objects in a video stream. Haar- like features are used to train the classifier from the training image set. Haar-like rectangular features are extracted and these features are used to train the method to track moving objects from video sequences using particle filter. Proposed method is tested on standard data sets: KTH, Caviar data set. The experimental results show that the proposed method can track multiple objects in a video adequately fast in the presence of poor lighting conditions, variation in poses of objects, shape, size etc. and the technique can handle varying number of objects in a video at various points of time.

Keywords – *Object tracking, video, surveillance, human detection*.

I. INTRODUCTION

In computer vision object tracking is a growing research area and useful for applications such as surveillance, vehicle navigation and traffic monitoring [9]. Object tracking is a process in which an object moves one place to another in video frames. Moving objects looks different from each other in shape, color and motion [1]. The background motion mobile objects are registered and research in tracking operation [4]. The main target of the object tracking is approximate the location and video sequence set in the starting frame [10].

Mainly the use of object tracking is for automated surveillance, video indexing, human-computer interaction, traffic monitoring, and vehicle navigation. Application of object tracking could be helpful regarding: Apply security policies, biomedical research, and vehicle routing, traffic information, surveillance, and mobile robot, educational and manufacturing industries. The major issues in object tracking are loss of information caused by estimate of the 3D world on a 2D image, noise in an image, difficult object motion, complex objects structures and real-time processing requirements.

II. RELATED WORK

Ashish khare et al. [1] proposed shearlet transform which combines shape based, color and motion based feature extracted using HSV color model and Adaboost with context sensitiveness to improve accuracy. Also, Tram Tran Nguyen Quynh [6] using HSV color model for feature extraction and Adaboost for training proposed a particle filter based model for object tracking. Fabian Sigges and Marcus Baum et al. [3] a likelihood-free used for huge amount of particles in the state space is analysis from the prior, measure space and compare both and calculates the OSPA distance in ABC particle filter to deal with different cardinalities.

A non-Gaussian recursive Bayesian Particle filter method is used to track moving objects based method proposed by Aashish Sharma et al. [4] for color based detection by isolating the moving color pixels from static background.

More over multi-features human tracking based on Hypothesis Density filter which help to accurately and robustly tracking under different environment by Tassaphan Suwannatat and Krisana Chinnasarnet al. [5].

According to Atsushi Yoshida et al. [7] kinect images using particle filter for color and depth information. Where as HamdAit Abdelali et al. [10] use this (particle filter) method for moving object in different situations. Apart from this Ding Dongsheng et al. [11] used particle filter method with color and texture feature to track object and result show in LBP texture histogram. Decide this for same method use for fixed shape of moving objects then moving object in video frame by Haris Masood et al. [12]. Up to that particle used by Mir Abbas Daneshyar et al. [13] for modified, distribution of moving objects it also used existing observations for color histogram model. HOG features used by redetection and pre-trained detection tracking method for different purpose. Redetection used by Di Yuan et al. [8] for target re-location and pre-trained detection used by Abdul-Lateef Yussiff et al. [15] for detect the human location in video frame. Redetection and pre-trained detection using HOG features for different purpose. Based on feature and location fusion a particle filter method proposed by Peng Tian [9] to compute the final location of object using simple features of the object similarity matrix.

Human tracking is introduced by Tassaphan Suwannatat et al. [14] for find unexpected movement human that show in camera this features is help the human location.

III. METHODOLOGY

Tracking can be explained as the problem of not accurate the path of an object in the image plane as it moves in a scene. The purpose of object tracking is to operate the route for an object by finding its position in every single frame of the video. Here, we have plans to modify a particle filter algorithm to track object in every frame of the video. In the present an approach, unpredictability about human's position is represented as a set of weighted particles, each particle representing one possible state. The filter generate particles from frame j-I to frame j using a motion model, determine a weight for each propagated particle using an appearance model, then re-samples the particles according to their weights. The continuous distribution for the filter is centered on the location of the object, detected first time. We have used following steps in proposed algorithm.

1. Collection of dataset
2. Feature selection
3. Modified Particle filter based method

1. Collection of dataset

To train the classifier the sample images datasets are collected first. We have collected a positive and negative image samples for training. The positive images in which the human objects contains and the negative images in which the any human objects does not contains. Our positive dataset consists of 2,560 images and negative dataset also consists of 2,440 images. Some collection of human images from positive samples is used for training the human detector.

2. Feature selection

We have used Haar-like features and rectangular features for multiple object tracking. These features have their intuitive similarity to the Haar-wavelets. Fast feature evaluation is used for representing the integral image. After computation of integral image description, training the human detector with use of adaptive boosting technique. The main motive for using Haar-like features is their easy estimate.

3. Particle filter creation for tracking

Particle filter has been used for tracking purpose. In the present an approach, unpredictability about human's state is represented as a set of weighted particles, each particle representing one possible state.

- *Selection:* N particles in an operation where the object is likely to locate at, and each particle has the same probability. As a show, 1000 particles are used for initialization.
- *Prediction*: Each particle is modified according to position model. If $\gamma_{a,b}$ and $\gamma_{a,b-1}$ represent the positions of an object a in b and a-1 frames then a propagation $\theta1(\gamma_{a,b} | \gamma_{a,b-1})$, over human object's a position in frame b, is estimated using the belief of its position in frame a-1. We define a motion model for estimating the position of a human object from frame to frame, We use a second-order auto-regressive dynamical motion model for object's position estimate in frames. Non-Gaussian noise is supposed in our motion model by a random noise variable. In this autoregressive motion model we expect the next position δ_i of the system as a function of some previous postion and a noise random variable $\theta1_t$, as given below:

$$\delta_i = f(\delta_{i-1}, \delta_{i-2}, \ldots \delta_{i-p}, \theta1_j) \quad (1)$$

We build a second-order linear autoregressive model for estimating the position of an object in current frame by using the information of its position in the last two frames as shown in equation (2).

$$\gamma_{j,i} = 2 * \gamma_{j,i-1} - \gamma_{j,i-2} + \theta1_i \quad (2)$$

- *Likelihood*: Calculate the each particles weights and sum of particles weight equal to 1.We measure the likelihood $\theta1(\beta^k | \gamma_{j,i}^{(k)}, \beta_j)$ generate particle k using a color histogram-based appearance model, where β_j is the color histogram in appearance model of trajectory j and β^k is the observed histogram. The likelihoods of generate particles is treated as weights, which are normalized in such a manner that their sum equals to 1.
- *Re-sampling:* The weights of the highest particle tend to weight of one and weights of other particles tend to zero. To avoid this poorness in weights, the particles are re-sampled.

In re-sampling, low weight particles are removed and higher-weight particles are replicated in order to obtain a new set of equally- weighted particle.

– *Appearance Model:* The appearance model is used for color histograms. For each newly detected human object a color histogram β^k is completed. In the future frames, the particle likelihoods are completed using color histograms so we save all the completed histograms. A particle's strong possibility is computed using the Bhattacharya similarity coefficient between the model histogram β^k and observed histogram $^{\beta(k)}$ assuming that there are n bins in the histogram. The likelihood $\theta 1(\beta^k| \gamma_{j,i}^{(k)}, \beta_j)$ of particle k is given as:

$$\theta 1(\beta^k| \gamma_{j,i}^{(k)}, \beta_j) \ \alpha \ e^{-d(\beta,\beta^{(k)})} \qquad (3)$$

$$d(\beta_j|\beta^{(k)})=1-\sum_{b=1}^{n} \sqrt{\beta_{j,b}\beta_b^{(k)}} \qquad (4)$$

Algorithm

1. Let K be the input video
1.1. In first frame n_o of K, detect humans using the human detector. Let w be the number of detected humans.
1.2. Initialize trajectories ∂_j,1≤ a ≤w; with initial positions $\gamma_{j,0}$ of the human beings detected by the detector and also set the occlusion count $\acute{\O}_j$ for each of these trajectories to 0.
1.3. Initialize the appearance model β_j for each trajectory from the region around $\gamma_{j,0.}$
2. For each subsequent frame n_i of input vide K, For each existing trajectory ∂_j.
2.1. Use motion model to predict the distribution $\theta(\gamma_{j,i}| \gamma_{j,i-1})$, over locations for human j in frame i,
creating a set of candidate particles $\gamma^{(k)}{}_{j,i}$,1≤ z ≤Z.
2.2. Use appearance model to compute the color histogram $\beta^{(k)}$ and likelihood $\theta 1(\beta^k| \gamma_{j,i}^{(k)}, \beta_j)$,If FJ for each particle z.
2.3. Acquire z*, the index of the most likely particle, after re-sampling the particles according to their likelihoods.
2.4. Now run the human detector on the location $\gamma^{(k^*)}$. If the location is classified as a human, reset $\acute{\O}_{j->}0$; otherwise increase $\acute{\O}_j$-> $\acute{\O}_{j+}1$.
2.5. If $\acute{\O}_j$ exceeds a threshold, remove trajectory j.
3. Now for frame n_i search the new human objects and compute the Euclidean distance $Q_{j,k}$ between each newly detected human z and each existing trajectory ∂_j. When $Q_{j,k}> \Phi$ for all j, initialize a new trajectory for detection z. where Φ is a threshold in pixels whose value is less than the width of the tracking window.

IV. DATASETS

In the proposed method we have used two datasets namely KTH and CAVIAR. In the KTH dataset Crowd surveillance events within a real-world environment includes estimation of crowd person count. In the CAVIAR dataset a number of video clips were recorded acting out the different scenarios of interest include people walking alone, meeting with others, window shopping, entering and exitting shops.

Table 1:Description of datasets used for experimentation

Video Seq-uence	**Information with respect to object**				**Information with respect to scene**	
	Object Type	***Object Type***	***Scene Type***	***Details of frames and objects***	***Noise Level***	***Comp-lexity***
	Person Walking	Large	Out - door	No. of frames = 741 Size of frames = 160 x 120 No. of object in frames = 1	High	Medium
	Person Walking	Large	In - door	No. of frames = 1996 Size of frames = 480 x 272 No. of object in frames = 3	High	Medium

Table 2: Confusion Matrix for KTH dataset

Objects / Objects	Human	Not Human
Human	89%	0
Not Human	0	0

Table 3: Confusion Matrix for Caviar dataset

Objects / Objects	Human	Not Human
Human	95.85%	0
Not Human	0.09%	0

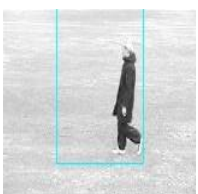
V. EXPERIMENTAL RESULT

Particle filter with sequential importance re-sampling is adopted for the people tracking. Tracking is the process of locating moving objects or multiple objects over a period of time using a camera. The tracking process starts when an object is detected for number of conservative's frames of video.

Technically, tracking is the problem of estimating the trajectory or path of an object in the image plane as it moves around a scene. The experiment was performed in a poor lighting environment. Proposed method is implemented on s laptop computer with configuration of i3 processor, 2GB of ram. Method tested on multiple real times outdoor and indoor videos.

The human predicting and tracking results in outcome with some videos are given in fig. 1, and fig. 2. Video automatically starts without any initial parameters. We have shown in fig. 1 the human predicting and tracking results with a realistic video consisting of person walking towards the camera. The video was shot at a resolution of 160x120 and a frame rate of 25 frames per second. We have shown in fig. 2 the human predicting and tracking results when the humans appear a video consisting of person walking towards the camera in indoor environment. The video was shot at a resolution of 480x272 and a frame rate of 29 frames per second.

In the experiment and result we have shown, the results in two datasets are: KTH, Caviar dataset. The result obtained in these dataset are better than in comparison other proposed method.



Frame 29

Frame 31

Frame 33

Frame 35

Frame 37

Frame 39

Frame 41

Figure1: Predicting and tacking results of the proposed method on a real time video in outdoor environment.

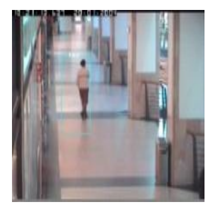
Frame 13

Frame 16

Frame154

Frame 160

Frame 176



Frame553

Figure 2: People tracking result on CAVIAR dataset in indoor environment.

Table 4: Comparison between existing methods and proposed method

Name	Evaluation Criteria	
	objects used	Accuracy
Ashish khare et al. [1]	Objects: Human	85%

Abdul-lateefyussiff et al.[15]	Objects: Human	77%
Proposed method	Objects: Human	89% at KTH dataset 95.85% at Caviar dataset

VI. CONCLUSION

In this paper, we proposed a modified particle filtering method. The original particle filter was a successful implementation for real-time visual object tracking. It causes a crude approximation of the posterior distribution, when the prior and posterior distributions have a large difference. This problem often occurs in real-time visual object tracking tasks due to the target's feature which is slightly changed in model. In addition, tracking method was analysis through a real-time tracking of a human in front of a moving camera. The proposed method was tested on standard datasets like KTH, and Caviar dataset. The proposed methods have a good degree of tracking accuracy.

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