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Multi Object Tracking Methods Based on Particle Filter and HMM

Ravichandran.A[1]
PG Scholar
[1]Department of Computer Science and Engineering,
K.S.R Institute for Engineering and Technology,
Namakkal, Tamilnadu,
ravichandrana31@gmail.com

Dr. B.Kalaavathi[2]
Head of the Department
[2]Department of Computer Science and Engineering,
K.S.R Institute for Engineering and Technology,
Namakkal, Tamilnadu,
kalabhuvanesh@gmail.com

Abstract – For various application detection of objects movement in a video is an important process. Determination of path of object as time advances is a tedious step. Many proposal for tracking the multiple movement of object has been put forward using various sophisticated techniques. In this paper detail description of the recent object trackers based on particle filtering and Markov Models have been analyzed. The outcome of the analysis is computational efficiency, robustness and computational complexity.

Index Terms – True Positive (TP), False Positive (FP), Markov Chain Monte Carlo (MCMC), Particle Filter (PF), Finite State Machines (FSM), and Hidden Markov Model (HMM).

1. INTRODUCTION

THE Movement orientation and path of the object can be detected by using advanced multi object tracking methods. The probabilistic characteristics of the object tracking algorithm helps in detecting and predictable and unstable trajectory of the object in the video.

Tracking of the object in the video can be done using the following steps: 1) choose a feature to describe the objects, 2) Detect the object of interest, 3) Track those objects for every frame, and 4) Analyze the tracking which fetches the behavior.

In this paper, the broad explanation of multi object tracking methods are put forward.

2. RELATED WORKS

2.1 Object Tracking Parameters

Some of the techniques are approached for object tracking [5], [17], [3], [2], [4]. Some of parameters in an object tracking are True Positive (TF) and False Positive (FP).

We can compare and spot true positives (TP) and false positives (FP) when the object be tracked manually segmented. False Positive also known as false alarm. *False reduction* is represented by TP and FP. A tracking accuracy of the multi object tracker is determinedby false reduction analysis. The ratio of false positive detection that can't be adapted to any ground truth trajectory over number of detections known as *false positive rate*. False positive rate is also known as *false alarm*.

2.2 Multi Track Linking

Data association is an important process for tracking large group of objects [6]. The main problem that occurs during the data association process results in "track switch" or "track lost" errors.

Once the long term occlusion occur individual or multiple tracks become merged and there after separated into individual tracks. Integrity of the splitting process is maintained by the "track linking method" which assumes each track as "tracklet" and links these tracklets.

Earlier approach known as local linking strategy was adopted to calculate pairwise cost between tracklets in a repetitive manner [8], [17], [7]. Track graph introduced by Nillius*et al*[9] and a Bayesian network interference algorithm as global linking strategy. Global linking as computationally expensive process that allows simultaneous matching of various tracklets.

Probabilistic association method takes into account, the optimization of integers. A problem of linear network is done by appropriate measurement to measurement match dealing with pairwise correspondence [23], [5], [24]. The solution to this problem can be achieved from semi definite programming [25] or arbitrary greedy search [26].

The data association technique are sub divided into sapling based algorithms. Oh *et al*[27] used Morkov Chain Monte Carlo (MCMC) to particulate data association hypothesis and track large number of objects.

The huge problem size for batch processing is a drawback in measurement level of data association methods. A sliding window access a tradeoff between batch size and accuracy [11]. The framework of the temporal data association that extended to tracklet level, where matched unit consist of the pair of trajectory segment [12]. Between the track fragments at each level *local* links are produced in the temporal data association approach [7], [28]. But, Nillius*et al*., [9] processed the track graph globally which defines all the object interactions.

2.3 Particle filter based Multi Object Tracker

The extended objects are bigger than conventional point tracking method and these are also used as objects in multiple object tracking methods. For multiple object tracking we need to create point measurements relative to 'extended' object reductions and apply one of the existing point object tracking algorithm. Commonly used object tracking methods are PHD (Probability Hypothesis Density) filter [14] and JPDA (Joined probabilistic Data Association)[13].

Comaniciu*et al*[15] put forward weighted histogram calculated from a circular region. Nummario*et al* [29] for tracking colored objects proposed a particle filter for single colored objects and manual initialization. [57] With the help of color and PF with automatic object initialization and deletion [16] color based probabilistic tracking is implemented.

2.4 Long Term Online Multiface Tracking using Particle Filter and HMM

In present years most of the multiface detector are applicable only when the person look towards to the camera. It is tough to track the trajectory of the object when difficult head postures which last for long are maintained.

Many multiple face tracking method has been put forward([16, 28, 5]), which mainly concentrate on better dynamics or adapted models ([2, 18, 19]). The results are based on only short video sequences.

The track termination and track initialization are addressed by multi object trackers for performance evaluation. Missing an early track initialization may be due to high confidence threshold in face detectors. Conversely, false tracks mainly occurs due to low threshold false track.

3. PARTICLE FILTER AND HIDDEN MARKOV MODEL FOR RECENT MULTI OBJECT TRACKING METHODS

In the field of robotics, Medicine and Weather tracking various multi object track methods are used. These are mainly used for fast and arbitrary motion of objects in video sequences. Each multi object tracker has its own advantages and disadvantages for adapting to a particular purpose and field of applications.

A. Multi Object Tracking Based on Coupled Layer Utilizing HMM and Sequential Particle Filter

Based on object tracking method coupled layer designed which consist of local and global layer. This coupled layer is adaptive to the objects global and local appearance [19]. The local layer uses the local information and global layer uses the global information.

Changes in target's appearance geometrically is limited by the local layer that comprises group of local patches. Addition removal of local patches update the whole structure. Global layer governs addition of patches. The global layer also models the objects global visual elements same color motions. The local layer updates the stable patches and global visual elements.

The addition of new patches is done by local layer done with the constrained effort of the global layer. Probabilistic model is required to overcome this constrain. To delimit the allocation of new patches in the local layer sequential particle filter scheme and Hidden Markov Model (HMM) is combined with the coupled layer object tracker [20].

1) Overview of Multi Object Tracker:The target object geometric information is focused by the local layer and initialization of the particle filter passes the information from the local layer to global layer.

Local layer patches are detected by the sequential particle filter and HMM at global layer and stores the sequence of the deformation information.The tracking efficiency of the multiple objects to the global layer improves this enhancement. Using distributed multi object tracking and high order Markov Chains, Sequential particle filter functions as a video tracker.

The guessing of the local layer patches during the tracking is essential to initialize the adaption of visual model. Assumptions of the target object's center is made as the weighted average of the patches position. For initialization of the local layer HMM is applied for global layer prediction and sequential particle filter. The prediction performance is enhanced by integrating particle filter localization with HMM prediction. And there by decreases the time consumption using predetermined memory allocation and the position of detected objects are stored.

2) Narration of the Multi Object Tracker:The various module of the multi object tracker include loading the video sequence frame conversion particle filter implementation and HMM. The system architecture of the object tracker is shown in the figure 1.

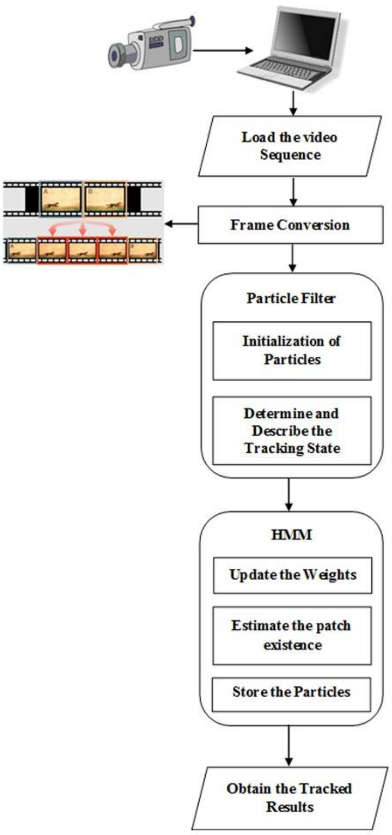

Figure 1. System Architecture of the Multi-Object Tracker

a) Loading a video sequence: The input video sequence consist of a stack of the images separated by time frames. Using *mmread()* function in MATLAB images sequences is loaded. With the creation of reader object we can read the image stack. The video file can be of any extension. *mmread()* function has parameters such as bits, pixel, duration, height, width, number of frames and inputs image sequences.

b) Particle filter Implementation: By a group of weighted particles the particle filter approximates the filter posterior distribution of images in the image stack. Using the prediction of previous frame patches locations the local layer patches are initialized by the particle filter and they are weighted based on a motion model.

The state of the system is represented as in equation 1, estimated using Markov Model a time x_t.

$$E(t) = P(x_t \mid y_{0\text{-}t}) \quad (1)$$

Here, E (1) can be initialized by the prior knowledge. Observations are depended only on the current state and it's independent of the past and future state. It's represented in the equation 2.

$$E(t) = P(y_t \mid x_t) * P(x_t \mid x_{t-1}) * E(t-1) \quad (2)$$

Where $P(y_t \mid x_t)$ is observation model and E (t-1) is the proposal distribution. The proposed framework requires attributes such as Observation model, Motion model and Initial model. The samples should be weighted by a ratio of posterior and proposal distribution. For the current frame rate of the particle it should be changed depending on the observation of the current frame. In the proposed method particle filtering has used as Sequential Monte Carlo simulation.

The following steps are carried out by the particle filter:

- Initialize x_t for the first frame
- Generate particle set consisting of N particles i.e. $\{x_t^m\}_{m = 1, 2, \ldots N}$
- Predict each particle (Using 2nd order auto aggressive dynamics)
- Compute distance between each particle
- Weight each particle depending on distance
- Select the location of target as a particle, which has minimum distance

c) Implementation of Hidden Markov Chain: For Prediction and global layer the Markov process used in sequential particle filtering techniques is not suitable. The past states do not have any influence on the present states in the Markov process

Let $\{x_t$: t is in T$\}$ be a stochastic process with discrete state space S and discrete time space T. The time space satisfies Markov property $P(x_{n+1} = j \mid x_n = i_{n-1} \ldots x_0 = i_0) = P(x_{n+1} = j \mid x_n = i)$ for any set of states i, j in S and $n \geq 0$ is called Markov chain.

The target's global visual features is encoded by the allocation of patches in the local layer. This scenario deems the model as hidden as there is no direct effect on the change of the states. In this model we can observe emission of the changes in the state.

A probabilistic HMM uses the following representations:

- A set of states over time, denoted by *STATES*
- A set of *emissions*, or observations over time, denoted by *SEQ*
- An *M*-by-*M transition matrixTRANS* whose entry (i, j) is the probability of a transition from state u to state j.
- An *M*-by-*Memission matrix EMIS* whose i, k entry gives the probability of emitting symbol s_k, given that the model is in state i.

In the memory information regarding patches in the frames is stored. Using the HMM the various patch information is tracked. The Finite State Machine (FSM) is used to represent the model. In a video sequence the FSM states tracks information in the different patch information. We can denote states in the Finite State Machine using memory locations of the stored patch information. The details regarding the transactions are denoted in the edges that exist between the states. The states are analyzed for thelocation of the required memory patch information for tracking the previous step.

3) Merits of the Multi Object Tracker: The prediction performance is enhanced by the combination of the HMM prediction with the particle filter localization and thereby limiting the time consumption. The computational complexity is decreased by storing detected objects using cell array memory, which in turn increases robustness of the system.

4) Demerits of the Multi Object Tracker:The computational time of the Multi Object Tracker is less compared to the recent multi object trackers. The number of the object track in the video sequence is also limited. The occlusions and multiple views of the camera is not resolved in multi object tracker. The false positive analysis was conducted only for first few frames and not for the entire video sequences.

4. RESULT AND DISCUSSION

The comparison of performance and computational analysis of different multi object are tracked. Computational complexity, computational time and time complexity, false positive and robustness are compared.Multi Object Tracking on Coupled Layer Utilizing HMM and Particle Filter Rapid video sequences containing different number of objects in different frames are tracked by means of multi object tracker. MATLAB on an Intel Core 2 Duo processor is used for framework implementation.

***1) Computation Time*:** 1.7731ms be the expected average time for processing single frame. The computation time analysis in MATLAB is given in figure 2.

2) False Reduction: First few frames of video sequence is implemented in MATLAB by means of false reduction analysis. The average true positive is 8.3 and average false positive is 1.08 be the expected computational result for multi object tracker. The false analysis of the video sequence in MATLAB is given in the figure 3.

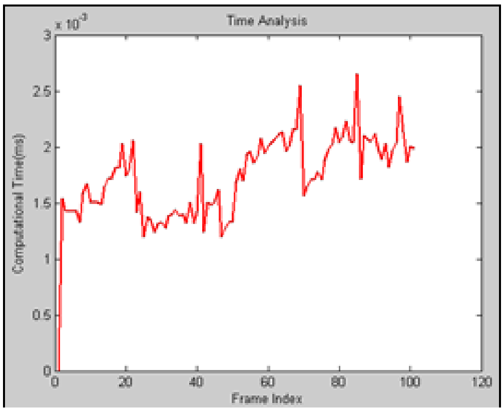

Figure 2. Computational Time Analysis

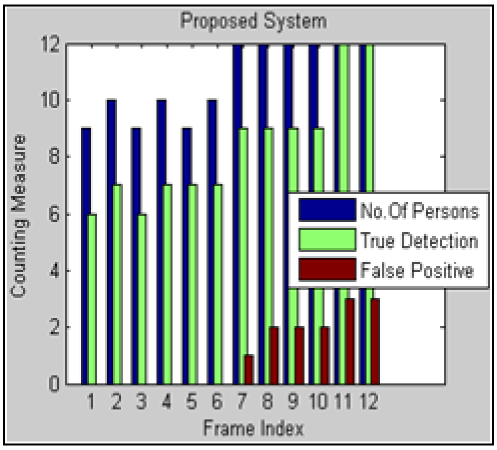

Figure 3. False Reduction Analysis

5. CONCLUSION

Along with the supporting context multi-object tracking methods based on particle filter, Hidden Markov Model (HMM) have been used. Path-based recognition, video referencing and automatic surveillance, smart cameras [21], human automation and vehicle interaction [22] are some of the uses of multi-object tracking methods. Computational efficiency, robustness, computational complexity, computation time, false positives are the factors considered when recent multi-object tracking methods compared to predecessors. Developing algorithms are the specific needs for object tracking methods. Video can suppress the noise when audio is combined with it for some noise in the videos.

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