

Using Adaptive Particle Filter Handling Occlusion in Video Surveillance

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Abstract- In video surveillance systems major performance decline is Occlusion. Occlusion should be detected very precisely by all automatic software system. Also automatic system continuously monitors the scene. When two objects are overlap, rear object will be hidden behind the front object .The hidden part of the rear object is called a occluded part the object. Human bodies are overlapped when they are walking in the scene. Illumination can be the reason for the occlusion because object identified by the intensity value of particle which belong to the object. Occlusion is not directly detected problem. Pixel of the occluded is detected which belong to the part of the same. Purpose of detection of Occlusion is mainly for the set occluded part in the image and gets the original image. Exquisite resampling is used for the improve the performance of the algorithm. Included phase in the algorithm is such like prediction, importance sampling and resampling . Optical flow is used for the finding important particle which can give both intensity and the direction of the particle.

Index Terms – Occlusion, Particle Filter, Resampling

I. INTRODUCTION

Image processing is used for different operations for digital phase and doing operations on the image, for getting good result it will detect helpful data from it. We are providing the video, frames as input and the output will be concerned characteristics of image. The image processing system contains as two dimensional signals treated as image for live methods of signal dispensation will be apply to them. Nowadays, It is one of the best increasing technologies, with its applications in a variety of branches of a business. Frames are detected, recognized by using Visual surveillance system with image processing. This type of structure is largely used in applications such as safety for major construction forces areas which can be detected and monitored travel in cities creatures. Analysis of video has been done by the recording of the video.

The occlusion is one of the main problems of reduced performance in video surveillance systems. Every mechanized discovery systems must precisely control occlusion. Two object is moving in the environment they overlapping each other due to that reason rear object will not be detected .It is called Occlusion. It has three types self occlusion, inter-object occlusion, back ground occlusion. Due to occlusion different parts such like animal, tree, vehicles will be overlapped in a scene.

Particle filter is based on Monte Carlo theorem. It estimates state by posterior probability, commonly used in pattern recognition and object tracking, such as [1].Improved from [2], this paper proposed an adaptive particle filters tracking algorithm scheme with exquisite resampling.

II. ADAPTIVE PARTICLE FILTER

In this Section, We will illustrate proposed algorithm the detail. Figure[1] is show the flow chart of the adaptive particle filter. It has three basic steps .1.prediction 2.importance sampling and resampling

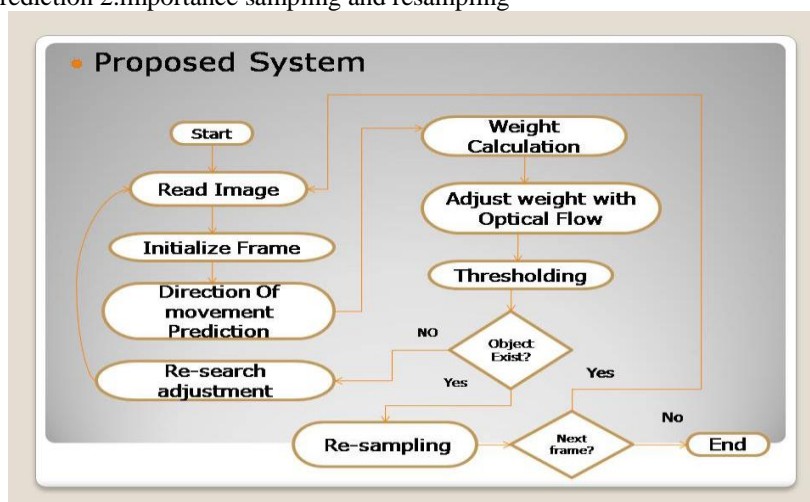


Figure [1]Proposed system

Particle Filter

Tracking objects in video involves the modeling of non-linear and non gaussian systems. One solution can be employed by using a probabilistic framework which formulates tracking as inference.[3] They are sequential Monte Carlo methods based on point mass representations of probability densities, which are applied to any state model [4]. Particle Filter is a hypothesis tracker, which approximates the filtered posterior distribution by a set of weighted particles. It weights particles based on a likelihood score and then propagates these particles according to a motion.

Weight of each particle should be changed depending on observation for current frame. The basic Particle Filter algorithm consists of 2 steps: Sequential importance sampling (SIS) and Selection step. In SIS step it uses Sequential Monte Carlo Simulation. For each particle at time t , transition priors are sampled. For each particle we then evaluate and normalize the importance weights. In selection steps (Resampling), we multiply or discard particles with respect to high or low importance weights to obtain a predefined number of particles. This selection step is what allows us to track moving objects efficiently .[4]

Prediction

The first stage of particle filter is prediction stage. When object disappears, instead of randomly spreading particles, we radially spread particles from where object disappeared because of the assumption that the object will not move faraway immediately. If the object is temporarily occluded, the way we spread particles research the target more efficiently than searching globally. While in long-term occlusion, we have already spread particles globally and this can avoid missing the object.[6]

Then, use the motion vector obtained from optical flow to adjust the diffusion range. A high standard deviation of the motion vector indicates the object moves drastically, hence we need to enlarge the diffusion range as Figure 2(a). A low standard deviation indicates moving consistency, so the diffusion range could be shrunk, as Figure. 2(b).[7]

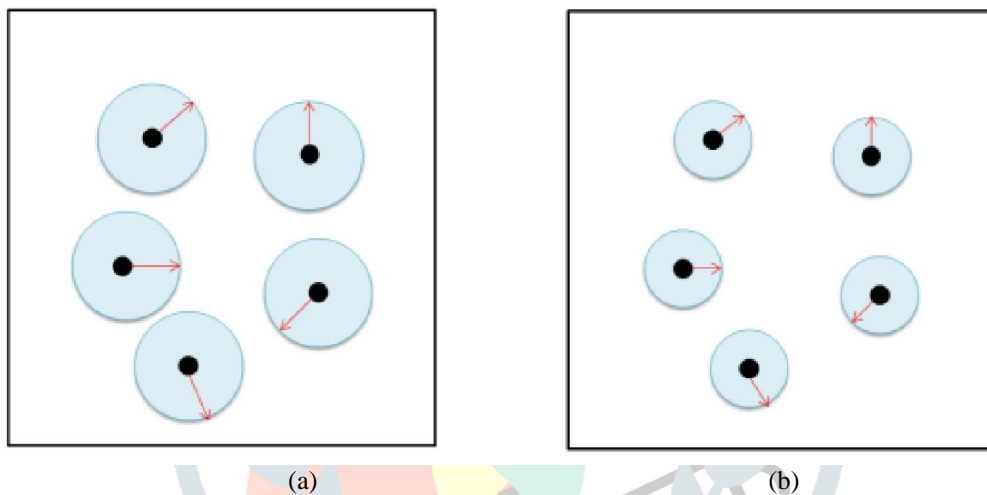


Figure 2 (a) high deviation for diffusion (b) low deviation for range

We can also predict the moving direction by motion vector. It is reasonable that the object moves toward the same direction according to the last few seconds, as a result, we spread the particles toward the same direction if moving direction has consistency.[6]

Sampling

Objective of this phase is find weight for each particle and also save important and discarded less important particle from. Color histogram of the target model is used as feature to determine the weights. It is called importance sampling. RGB histogram space used 8,8,8 bins also derived weights of the target model. Always centre pixel of the object is important compare to boundary pixel.[6]

After obtaining the original weights by calculating their Bhattacharyya coefficients, we take two steps to refine them. Optical flow [8] is the apparent motion of brightness patterns in the image. Ideally, it would be the same as the motion field. Calculating the average of motion vector [9] obtained from optical flow, we can predict a new centre from the last centre. Promoting the weights of particles around the centre which optical predicts is the first step.

The second step is to set a threshold. Low-weight particles decrease accuracy, to avoid it, we hope to eliminate those less important. A suitable measure of degeneracy of the algorithm is the effective sample size N_{eff} introduced in [1]. Using to obtain the effective samples, choose the lowest weight in those samples to set the threshold. The weight which is lower than the threshold is set to be zero .

When all the weights are small and set to zeros, means all the particles in the whole frame are not similar to the target, in other words, there exists no object.[1]

Resampling

Elimination of the small weight particle and give the importance to the higher value weight particle .This objective of this phase. Prediction is also depend on the high value pixel. Disadvantage of Resampling algorithm has represented in the fig.

N = number of particles [6]

C_i represents the cumulative sum of weights. U_i is a sequence of random variable which is uniformly distributed in the interval $[0,1]$. We view U_i as a threshold, the CDF crossing over it is considered the more important one. As shown in , Because C_2, C_4 and C_5 cross the threshold U_2, U_4 and U_5 . U_2, U_4, U_5 are saved for the use of next prediction. From the figure we can found that particle 2 weight lesser than particle 1. Particle 4 weight is lesser than particle 3. Estimation accuracy will be decreased due to this fault .From using the resampling ,problem will be solved. [10]

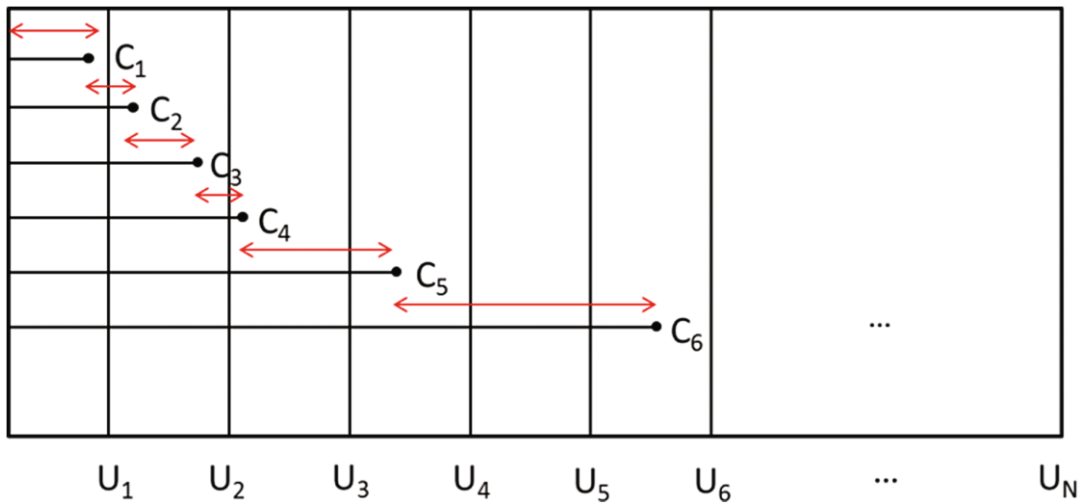


Figure. 10. Algorithm of resampling

Find out the particle which has high weight in that interval. C_1, C_3 eligible candidate to be saved .From this pdf can be very accurate .

We generate the dynamic state space equation which given below:[6]
 where v_k and w_k are nonzero mean Gaussian random variables,
 $x_0 = 1, \alpha = 0.5, \beta = 25, \gamma = 8$, sample numbers = 100, Time step = 50 s.

$$x_{k+1} = \alpha x_k + \beta \frac{x_k}{1+x_k^2} + \gamma \cos(1.2 k) + v_k \quad [6]$$

$$y_k = \frac{x_k^2}{20} + w_k \quad k= 1,2, \dots$$

Comparison of Particle filter and Adaptive Particle Filter

		Mean error	Accuracy
Experiment 1	Particle Filter	30.89	96.07 %
	Adaptive Particle Filter	19.97	97.38 %
Experiment 2	Particle Filter	47.54	42.60 %
	Adaptive Particle Filter	24.52	96.69 %
Experiment 3	Particle Filter	56	67.5 %
	Adaptive Particle Filter	38.4	99 %

III. CONCLUSION

Particle filter is mainly based on estimation of posterior probability. It is also useful for pattern recognition and object tracking. Using adaptive particle for object tracking scheme along with exquisite resampling, we can improve prediction and resampling. Refinement of particle weights are done by Optical Flow, using the dynamic state model for motion information. From that we can easily find out the future flow of the object. Proposed algorithm is improved and enhanced the image ,from the comparison table we can easily derive .

IV. ACKNOWLEDGMENT

I am very grateful and would like to thank my guide and teacher Prof. Hitul Patel, for his advice and continued support without them it would not have been possible for me to complete this paper. I would like to thank all my friends, colleague and classmates for all the thoughtful and mind stimulating discussions.

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