EFFECTIVE MOTION TRACKING OF MOVING PERSONS/OBJECTS USING MCMC SAMPLING METHOD

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Abstract

The robust tracking of the abrupt motion is a challenging task in the recent field of computer vision. For visual tracking various tracking methods such as particle filters and by using Markov-Chain Monte Carlo (MCMC) method have been proposed , but these methods grieve from the local-trap problem and abrupt motion un certainity. In this paper, we introduce the Stochastic Approximation Monte Carlo (SAMC) sampling method into the Bayesian filter tracking framework for handling the local-trap problem. In addition for improving the sampling efficiency, and propose a new MCMC sampler with intensive adaptation. This is done by combining the SAMC sampling with a density-grid-based predictive model. The proposed method is very effective and computationally efficient in addressing the abrupt motion problem. The proposed method is named as Intensively Adaptive Markov Chain Monte Carlo (IA-MCMC).The experiment results for various videos with single and multiple objects have been proposed.

Index Terms—*Abrupt motion, intensive adaptation, Markov chain Monte Carlo (MCMC), stochastic approximation, visual tracking***.**

1.INTRODUCTION

Video tracking is the process to locate the moving object over time by using a video camera. This has some uses which are Human computer interaction, Security and surveillance, Video communication, Traffic control, Medical imaging etc.Tracking refers to establishing the correspondences of the object of interest between the successive frames. In real world, many tracking tasks suffer from the multimodal likelihood and posterior, high-dimensionality and inaccurate local evidence. To facilitate efficient tracking, in general, most existing approaches are based on a smooth motion assumption or an accurate motion model. However, abrupt motions are common in real-world scenarios, such as fast motion, camera switching, low-frame-rate videos, and unexpected object dynamic.

It is challenging for tracking methods, both deterministic [2].[3] and sampling-based ones[10],[13], to deal with the large motion uncertainty induced by abrupt motions. Intuitively, a direct solution for the sampling-based tracking methods is to enlarge the sampling variance to cover the possible motion uncertainty. Nevertheless, there exists a problematic issue to be addressed, i.e., the sampling inefficiency. This is because the increase in the sampling volume may require a more expensive computational cost, particularly for the systems with the high-dimensional state space. The success of the PF highly relies on its ability to maintain a good approximation to the posterior distribution.The high computational burden caused by a large number of particles often makes the PF infeasible for practical applications. Markov-chain Monte Carlo (MCMC) methods have received much attention in visual tracking. A simulated annealing process [10] is incorporated into the conventional PF [14], which allows for the generation of the samples closer to the true modes of the posterior distribution and avoids the problem of getting trapped in local modes of the high-dimensional sample space for articulated body tracking.

To overcome the local-trapped problem, the adaptive MCMC algorithms have shown more superiority in improving the mixing and acceptance rates, even if much research is still expected in this exciting area. In principle, an adaptive MCMC algorithm aims to simulate a good chain, the distribution of which is closer to the target distribution by using the historical samples, and thus reduces the variance of the estimate of interest. Rather than simply adopt the sequential importance re-sampling (SIR)[14] or standard MCMC sampling algorithm, which is common for the state-of-the-art tracking methods, propose a more effective dynamic IS scheme to sample from the filtering distribution by using the stochastic approximation Monte Carlo (SAMC) [9] algorithm and present a sequential SAMC sampling algorithm for the tracking of abrupt motion, which demonstrates superiority in dealing with the local-trap problem with less computational burden.

For the proposed sequential SAMC[9] tracking method, however, to guarantee its robustness, a certain number of samples are still required to capture the abrupt motion due to the broadness of the whole state space. They propose a more effective sampling algorithm to further reduce the computational cost. They achieve this by introducing a density-grid-based predictive model, which carries the statistical information about the filter distribution, to predict the promising regions of the state space in sampling. Based on the predicted result, a more informative proposal is learned on the fly, which helps to bias the sampling toward the promising regions of the state space to improve the sampling efficiency.

2.BACKGROUND

Visual tracking is an important research area in computer vision. However, scenarios that contain rapid structural appearance changes present such models with serious difficulties. The reason is that such visual changes lead to reduced matches and drifting which eventually result in the trackers failure. To address these problems, approaches to tracking using sets of simple local parts have been proposed. It is challenging for tracking methods, both deterministic ones and sampling-based ones, to deal with the large motion uncertainty induced by abrupt motions. Intuitively, a direct solution for the sampling-based tracking methods is to enlarge the sampling variance to cover the possible motion uncertainty [8]. Nevertheless, there exists a problematic issue to be addressed, i.e., the sampling inefficiency. Here, the most relevant tracking approaches, focusing on algorithms that directly aim to deal with the abrupt motion difficulty. The simplest solution to the abrupt motion problem is searching the whole state space to fully cover the motion uncertainty. In practice, however, it is infeasible due to the large search space of the object state, which often results in an extremely expensive computational cost. Indeed, an accurate dynamic model can be used to estimate the search space based on the object state prediction.To overcome abrupt motion tracking problem, we introduce a novel sampling based tracking named as Stochastic Approximation Monte Carlo (SAMC) [9] sampling method. However, SAMC method may cause more computational cost. This can be reduced by introducing a density-grid-based predictive model. The combination of the SAMC [9] and density-grid model, which can be named as Intensively Adaptive Markov Chain Monte Carlo Sampling (IA-MCMC) method of tracking.

A .Initialization

Some applications create collections of images related by time, such as frames in a movie, or by (spatial location, such as magnetic resonance imaging (MRI) slices. These collections of images are referred to by a variety of names, such as image sequences, image stacks, or videos. The toolbox represents image sequences as four-dimensional arrays, where each separate image is called a frame, all frames are the same size, and the frames are concatenated along the fourth dimension. mmread function will be used for loading and showing the input video sequence.

B .Frame Conversion

The loaded video sequence should be converted into frames (i.e. still images) using mmreader function. To read the video information use the read function which reads the total information about the given video file. In this, the video is converted into 165 frames for the effective tacking.

C. Particle Propogation

In the particle propagation stage, a re-sampling process is first run on the input particles set generated at the previous time step to give a new particles set with equal weight. Based on this filtering distribution is approximated, then generate initial sample for the subsequent sampling operations. It is sufficient for our particles propagation to use such a weak transition model since our objective is only to produce an initial sample to characterize the smooth motion, and the abrupt motion can be covered by subsequent SAMC sampling operations.

D. SAMC Sampling Process

To give a clear view, the flowchart of the sequential SAMC sampling framework is schematically depicted in Fig. below. In the figure, the input video frames is firstly given to the particle propagation.

The output of this particle propagation is then given to the SAMC sampling. Then the output of SAMC sampling is given to the final step of SAMC sampling process, ie, sample reweighting.

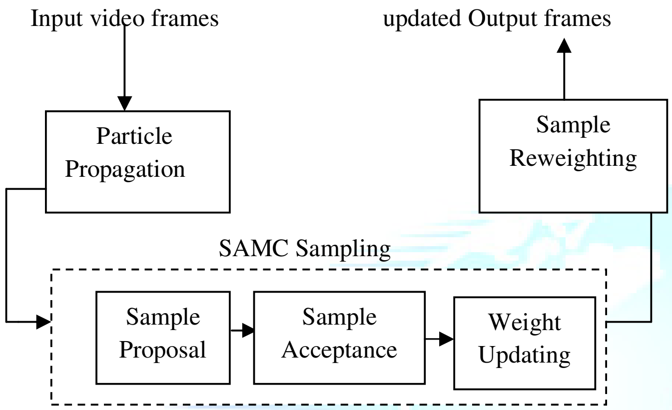

Figure 1: SAMC Sampling Process

In the SAMC sampling stage, it consists of 3 major consecutive steps. They are proposal, acceptance, working-weight updating. In proposal, the proposal distribution used for our sampling scheme should be carefully designed to account for the large motion uncertainty. The sample space of our filtering problem is compact and bounded. In acceptance, in this determine whether the candidate sample is accepted or not. If the sampling value is nearer to the current sample value, then that will accept or if the value is far away from the current sample The acceptance probability is defined as,

$$\alpha(X';Xt)=\min\left\{1,\ \frac{(Pg(X')\ Q(Xt;X')}{(\ Pg(Xt)\ Q(X';\ Xt)}\right\}$$

In working Weight Updating, once a new sample is simulated by the sampling process, a updating step for the working weight will be run to update the DoS of energy sub-region. Compared with the WL algorithm, SAMC shows more superiority in sampling efficiency due to its self-adjusting mechanism, which makes the sampling less trapped by local modes .Meanwhile, the weights of other energy sub-regions will be adjusted to a smaller value, and thus, the probability of jumping to one of these energy sub-regions will increase in the next iteration.

E. IA-MCMC Sampling

The sequential SAMC sampling algorithm can deal with the large motion uncertainty. To further improve the overall sampling efficiency, need to design a more efficient sampling algorithm. Based on the initial samples set generated by SAMC in preliminary sampling, the initial density grid is established, and the sample space is then initially grouped into promising regions and non promising regions. By introducing a SAP into the MCMC sampling framework, SAMC can effectively overcome the local-trap problem during sampling even when the energy landscape is rugged. IA-MCMC is a two-step sampling scheme that involves preliminary sampling and adaptive sampling..The preliminary sampling aims to discover the rough modes of the energy landscape.

The adaptive sampling is to refine the promising regions of the sample space and to thus guide the sampling around the posterior modes. The sampling–prediction–sampling scheme can be viewed as a data-mining-mode embedded sampling algorithm, which substantially speeds up the overall sampling process of abrupt motion tracking. Here, the density grid is selected to be the predictive model for searching the promising regions of the sample space because of its computational efficiency.

It should be noticed that this density grid is repeatedly used in the adaptive sampling step. The reason for the use of a density-grid-based predictive model in the SAMC sampling process lies in the fact that the density grid model aims to estimate the promising regions of the sample space so that the new samples generated from these promising regions will have more chances to reach the global optimum than one simply drawn by uninformative proposal operation over the broad sample space, whereas SAMC allows the sampling to explore the whole sample space and produce more representative samples.

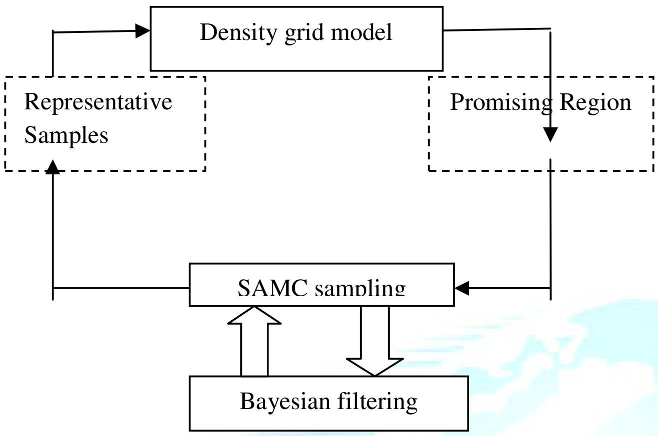

Figure 2: IA-MCMC Sampling Process

3. PROPOSED WORK

The motion of a model if it is hidden by an object is not mentioned in this paper. So inorder to overcome this disadvantage, a Hidden Markov Model of tracking is introduced. These Hidden Markov Models (HMMs) are learnable finite stochastic automates. Now adays, they are considered as a specific form of dynamic Bayesian networks. A Hidden Markov Model consists of two stochastic processes. The first stochastic process is a Markov chain that is characterized by states and transition probabilities. The states of the chain are externally not visible, therefore "hidden". The second stochastic process produces emissions observable at each moment, depending on a state-dependent probability distribution. It is important to notice that the denomination "hidden" while defining a Hidden Markov Model is referred to the states of the Markov chain, not to the parameters of the model.

Many times we don't have a direct observation of the change of the states. Therefore we say the model is hidden. By using HMM, we can track the hidden object exactly. By using HMM method, can eliminate the problem of merging of two person in a frame. In this, propose improved target localization by combining the local and global appearance of target. In order to predict a target, there must be a communication between global and local layer. And apply the Hidden Markov Model (HMM) for global layer prediction and Particle filter for initializing the local layer. This initialization is done by particle filter which makes use of the information from HMM which predicts the location of patches from previous frame. This enhancement to the global layer improves tracking efficiency And can separate the two person and mark it individually to track multiple human beings those are in moving state. The width and height of bounding box have to be varied in accordance with that of the position of corresponding human In this a fast moving video is first converted into required number of frames. Then HMM is applied to each of the frame. This made to update the frame information. By using these information, we can access the present and the past information of the moving object from a frame. According to the updated information of each frame, can estimate the location of the hidden person. By using this details can track the hidden person who made in occlusion. Thus, finally track the occluded person by using HMM. To track multiple human beings those are in moving state. The width and height of bounding box have to be varied in accordance with that of the position of corresponding human

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A. Loading video sequence

Some applications create collections of images related by time, such as frames in a movie, or by (spatial location, such as magnetic resonance imaging (MRI) slices. These collections of images are referred to by a variety of names, such as image sequences, image stacks, or videos. The toolbox represents image sequences as four-dimensional arrays, where each separate image is called a frame. mmread function will be used for loading and showing the input video sequence.

B. Frame Conversion

The loaded video sequence should be converted into frames(i.e still images) using mmreader function.All frames are the same size, and the frames are concatenated along the fourth dimension.

C. Particle Filter Implementation

The particle filter initialized the local layer patches by predicting the location of the patches from previous frame. It weights particles based on a likelihood score and then propagates these particles according to a motion model. Particle filtering assumes a Markov Model for system state estimation. Markov model states that past and future states are conditionally independent given current state. Thus, observations are dependent only on current state. Weight of particle should be changed depending on observation for current frame.

D. HMM model

The global layer prediction is made through HMM. Markov process is a simple stochastic process in which the distribution of future states depends only on the present state and not on how it arrived in the present state. The allocation of new patches in the local layer is constrained by global layer, which encodes the target's global visual features. For this purpose it maintains a probabilistic HMM.

4.RESULTS AND DISCUSSION

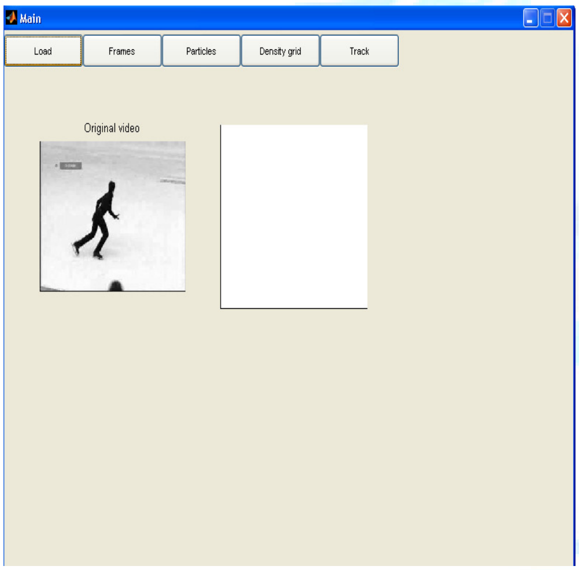

Fig 1: playing input video

In figure 1,here in existing system a fast moving video is used as input video, with sudden dynamic changes i.e fast movements.

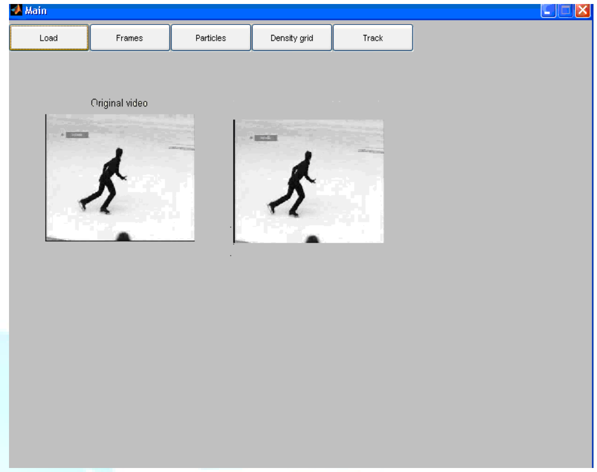

Fig 2:Frame Conversion

In the figure 2, in the existing system the input video,fast moving video is converting into number of frames. Here 165 frames are used for the effective tracking process.

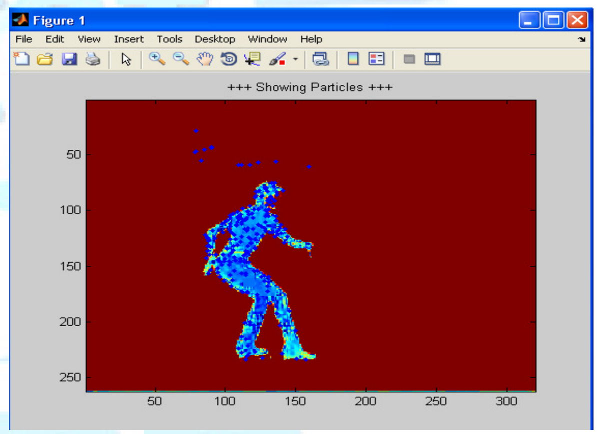

Fig 3: Existing system particles

In figure 3, the existing system particles are used. These particles will concentrate on the fast changing pixels in the frame. It will help to track the fast moving person or object in the video

IJREAT International Journal of Research in Engineering & Advanced Technology, Volume 1, Issue 5, Oct-Nov, 2013
ISSN: 2320 - 8791
www.ijreat.org

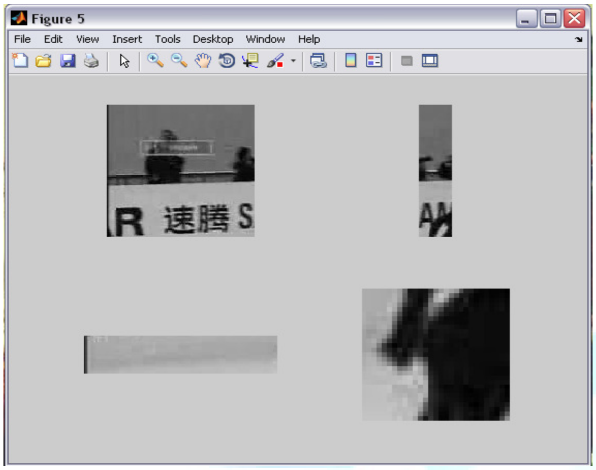

Fig 4: Applying density grid

Figure 4, shows the result of IA-MCMC sampling process. Density grid is used in this the adjacent frames which are used to compare the most promising regions for the effective tracking.

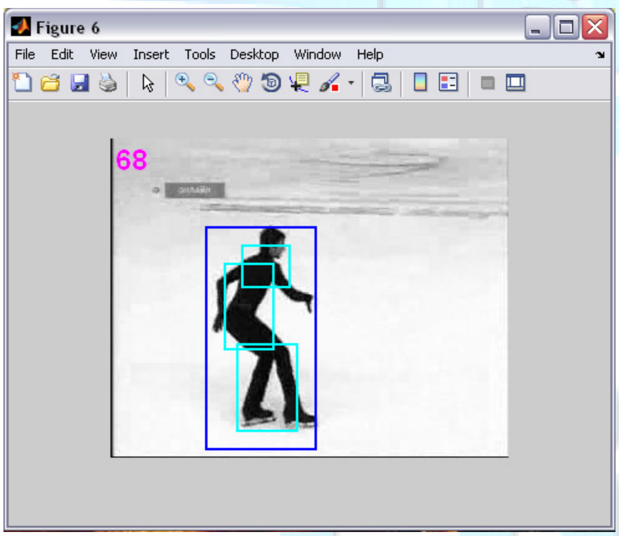

Fig 5: Single Person Tracking

In figure 5 shows in the existing system the effective tracking of the target in the input video. Here four rectangular boxes are used to show the tracking. Three boxes are used to represent the human or the target. Each box represents the Head, Torso and the Leg portions thereby covering the entire posture of the human.

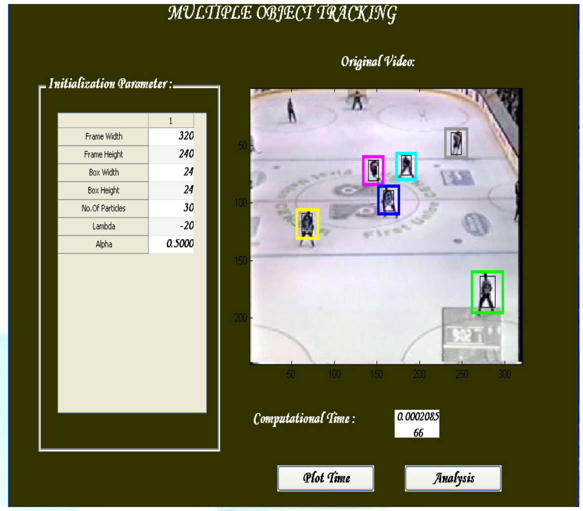

Fig 6: Loading and Tracking multiple persons video

In figure 6, here in the proposed system shows the fast moving video which contains occlusion where the object is hidden by another object in the input video.

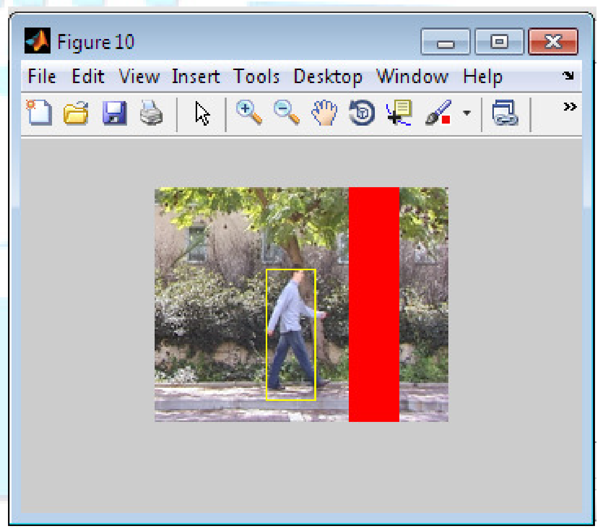

Fig 7: Single person tracking with occluded background video

In figure 7, this shows the tracking of moving object in the fast moving input video where some portion of the background is occluded. Even when the moving object gets occluded during the last few frames, and when the human gets occluded the tracking continues efficiently.

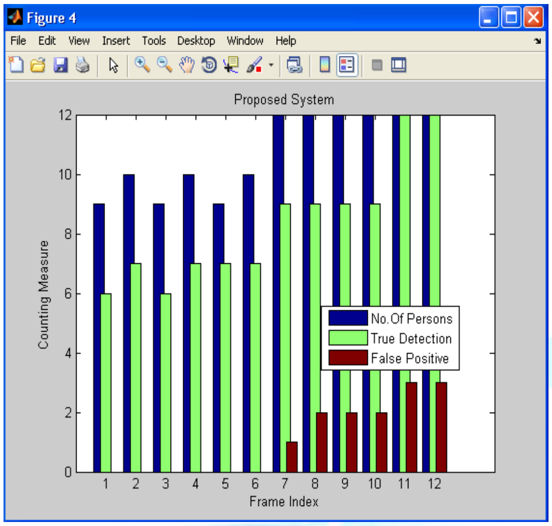

Fig 8 Graphical representation of proposed system

In figure 8, here in proposed system this shows the tracking of moving objects in the fast moving input video in graphical representation.

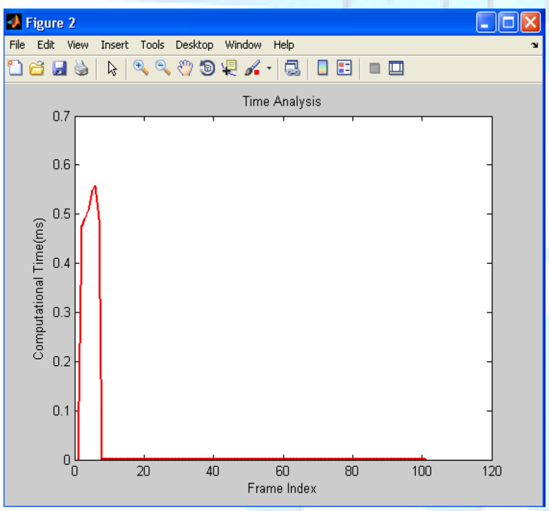

Fig 9 Time Analysis

In figure 9,this shows the time analysis between Frame index Vs Computational time tracking of moving objects in one frame for the fast moving input video.

5. CONCLUSION

Here present a novel approach for robust abrupt motion tracking in various scenarios. In this, the SAMC sampling method into the Bayesian filtering framework is used to solve the local-trap problem in sampling suffered by many existing sampling-based tracking approaches. Furthermore, the SAMC algorithm is extended to a MCMC sampler with intensive adaptation by learning the proposal on the fly in sampling. Extensive experiments have indicated that this method outperforms other alternatives and exhibit better efficiency and effectiveness in the tracking of abrupt motion. The moving object which is hidden by another object is not correctly explained in the existing system. So in proposed system for motion of a model if it is hidden by an object is track by using Hidden Markov Model. This enhancement to the global layer improves tracking efficiency and can separate the two persons and mark it individually to track multiple human beings those are in moving state.

REFERENCES

[1] M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, “A tutorial on particle filters for on-line nonlinear/non-Gaussian Bayesian Tracking,” IEEE Trans. Signal Process., vol. 50, no. 2, pp. 174–188,Feb. 2002.

[2] D. Comaniciu, V. Ramesh, and P. Meer, “Real-time tracking of non-rigid objects using mean shift,” in Proc. CVPR, 2000, pp. 142–149.

[3] C. Yang, R. Duraiswami, and L. Davis, “Efficient mean-shift tracking via a new similarity measure,” in Proc. CVPR, 2005, pp. 176–183.

[4] F. Wang and D. P. Landau, “Efficient multiple - range random-walk algorithm to calculate the density of states,” Phys. Rev. Lett., vol. 86, no. 10, pp. 2050–2053, Mar. 2001.

[5] F. Liang, C. Liu, and R. J. Carroll, “Stochastic approximation in Monte Carlo computation,” J. Amer. Statist. Assoc., vol. 102, no. 477, pp. 305–320, Mar. 2007.

[6] B. A. Berg and T. Neuhaus, “Multicanonical algorithms for 1st-order phase-transitions,” Phys. Lett. *B*, vol. 267, no. 2, pp. 249–253, Sep.1991.

[7] E. Maggio and A. Cavallaro, “Accurate appearance-based Bayesian tracking for maneuvering targets,” Comput. Vis. Image Understand., vol. 113, no. 4, pp. 544–555, Apr. 2009.

[8] A. Yilmaz, O. Javed, and M. Shah, “Object tracking: A survey,” ACM Comput. Surv., vol. 38, no. 4, pp. 1–45, 2006.

[9] F. Liang, C. Liu, and R. J. Carroll, “Stochastic approximation in Monte Carlo computation,” J. Amer. Statist. Assoc., vol. 102, no. 477, pp. 305–320, Mar. 2007.

[10] J. Deutcher, A. Blake, and I. Reid, "Articulated body motion capture by annealed particle filtering," in Proc. CVPR, 2000, pp. 126–133.

[11] J. S. Liu, F. Liang, and W. H. Wong, "A theory for dynamic weighting in Monte Carlo," J. Amer. Statist. Assoc., vol. 96, pp. 561–573, 2001.

[12]M. Yang, Z. Fan, J. Fan, and Y. Wu, "Tracking non-stationary visual appearances by data-driven adaptation," IEEE Trans. Image Process., vol. 18, no. 7, pp. 1633–1644, Jul. 2009.

[13] P. Perez, C. Hue, J. Vermaak, and M. Gangnet, "Color-based probabilistic tracking," in Proc. ECCV, 2002, pp. 661–675.

[14]. M. Isard and A. Blake, "Condensation—Conditional density propagation for visual tracking," Int. J. Comput. *Vis.*, vol. 29, no. 1, pp. 5–28,1998.

[15] Y. Li, H. Ai, T. Yamashita, S. Lao, and M. Kawade, "Tracking in low frame rate video: A cascade particle filter with discriminative observers of different life-spans," in Proc. CVPR, 2007, pp. 1–8.