Journal of Theoretical and Applied Information Technology
10th May 2014. Vol. 63 No.1
© 2005 - 2014 JATIT & LLS. All rights reserved·
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

NONRETINOTOPIC PARTICLE FILTER FOR VISUAL TRACKING

[1] ALEXANDER A S GUNAWAN, [2] ITO WASITO
[1] Bina Nusantara University, Mathematics Department, School of Computer Science, Jakarta, Indonesia
[2] Universitas Indonesia, Faculty of Computer Science, Depok, Indonesia
E-mail: [1]1, [2]ito.wasito@cs.ui.ac.id

ABSTRACT

Visual tracking is the problem of using visual sensor measurements to determine location and path of target object. One of big challenges for visual tracking is full occlusion. When full occlusions are present, image data alone can be unreliable, and is not sufficient to detect the target object. The developed tracking algorithm is based on bootstrap particle filter and using color feature target. Furthermore the algorithm is modified using nonretinotopic concept, inspired from the way of human visual cortex handles occlusion by constructing nonretinotopic layers. We interpreted the concept by using past tracking memory about motion dynamics rather than current measurement when quality level of tracking reliability below a threshold. Using experiments, we found (i) the performance of the object tracking algorithm in handling occlusion can be improved using nonretinotopic concept, (ii) dynamic model is crucial for object tracking, especially when the target object experienced occlusion and maneuver motions, (iii) the dependency of the tracker performance on the accuracy of tracking quality threshold when facing illumination challenge. Preliminary experimental results are provided.

Keywords: *Visual Tracking, Full Occlusion, Bootstrap Particle Filter, Color, Nonretinotopic, Tracking Quality Threshold*

1. INTRODUCTION

In this research, we consider the problem of tracking single object in video sequences using only one camera. In particular, we focus on the cases where target object occludes by other objects, either partially or fully. Partial occlusion hides some parts of the target while complete occlusion hides the entire target for some time. Many techniques exist to handle the occlusion problem with particle filter probabilistic models, such as in [1]. But the proposed tracking method uses network of many cameras to handle this problem. The other proposed tracking method [2] adds the adaptiveness of likelihood function and invariance of color distributions to particle filtering. Note that the target object can be rigid (e.g., car) or deformable (e.g., person).

The main question of the research is how to track object which overcome full occlusion in within finite period time. Inspired by human visual perception which shows that the representation of the visual cortex occurs in a nonretinotopic manner [3], we developed nonretinotopic particle filter. Visual processing is often assumed to be retinotopic, which means the visual process where object in the environment are projected to photo-receptors in the retina in a similar manner as appearance models in a digital image. Nevertheless, a recent study on human vision [3] shows that the representation in higher visual areas of the visual cortex occurs in a nonretinotopic approach: visual perception seems to create dynamic layers for each moving object in the scene. This representation suggests that the appearance of the objects and their positions are marginal independent. The nonretinotopic approach describes our visual processing that always maintains the identity of observed objects across space and time [4].

The implementation of visual tracking algorithm in this research is based on Bayesian framework, mainly bootstrap particle filter. Furthermore the algorithm is modified using nonretinotopic concepts. To evaluate and compare the capabilities of two tracking algorithms: generic and retinotopic particle filter, we use various video sequences and analyze the tracking performance. The paper is organized as follows: first we discuss the Bayesian framework and its implementation based on bootstrap particle filter. For observation model in experiments, it is used color feature of target object. Then, we consider the nonretinotopic concept and

Journal of Theoretical and Applied Information Technology
10th May 2014. Vol. 63 No.1
© 2005 - 2014 JATIT & LLS. All rights reserved·
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

how to modify the algorithm using this concept. Finally, we discuss the experiment results dealing with occlusions in general and with motion and illumination in particular.

2. TRACKING AS BAYESIAN PROBLEM

The problem of tracking moving objects visually can be modeled as a Markov process where one wants to estimate the value of a hidden state x_t} from a set of observations and a discrete time index t. The main purpose of the tracker is to estimate the distribution with the state of the target x_t is the position and the velocity of the object. Based on Bayes' theorem, object tracking problems can be described [5] as follows:

Prediction:

$$p(x_{1:t} \mid z_{1:t-1}) = p(x_t \mid x_{1:t-1})\, p(x_{1:t-1} \mid z_{1:t-1}) \tag{1}$$

Update:

$$p(x_{1:t} \mid z_{1:t}) = \frac{p(z_t \mid x_{1:t}, z_{1:t-1})\;\; p(x_{1:t} \mid z_{1:t-1})}{p(z_t \mid z_{1:t-1})} \tag{2}$$

2.1 Recursive Bayesian Solution

A recursive solution for this estimation problem is provided by the Bayesian framework. The above recursive Bayesian solution provides the posterior conditional distribution $p(x_{1:t} \mid z_{1:t})$ at time t, after receiving the last measurement z_t. The above prediction and update stages simplify under several assumptions. First, the measurements at a given time are conditionally independent of measurements taken at other times, i.e., the measurements at time t are independent of the measurements at times ≤ t−1, and that they depend only on the current states of objects via x_t and not on its entire state sequence, the measurement likelihood $p(z_t \mid x_{1:t}, z_{1:t-1})$ simplifies to $p(z_t \mid x_t)$.

In object tracking, it is usual to make simplifying the model adequately based on real−world system. Then it is assumed that the system follow a Markov process of order one where the present state does not depend on previous states, given the last state that is $p(x_t \mid x_{1:t-1}) = p(x_t \mid x_{t-1})$.

The main purpose in object tracking is to estimate the distribution $p(x_t \mid z_{1:t})$. This knowledge can be derived from $p(x_{1:t} \mid z_{1:t})$ by integrating out objects and their state. Then the above prediction and update stages [6] become:

Prediction:

$$p(x_t \mid z_{1:t-1}) = \int p(x_t \mid x_{t-1})\, p(x_{t-1} \mid z_{1:t-1})\, dx_{t-1} \tag{3}$$

Update:

$$p(x_t \mid z_{1:t}) = \frac{p(z_t \mid x_t)\;\; p(x_t \mid z_{1:t-1})}{p(z_t \mid z_{1:t-1})} \tag{4}$$

The denominator $p(z_t \mid z_{1:t-1})$ is the normalization factor that ensures that the resultant probability distribution $p(x_t \mid z_{1:t})$ satisfies the axioms of probability and sums up to 1. And the integral

$$\int p(x_t \mid x_{t-1})\, p(x_{t-1} \mid z_{1:t-1})\, dx_{t-1}$$

is the Chapman-Kolmogorov equation. The solution of this integral gives the predicted state of the elements of x_t, given all the measurements up to time t−1 and the state at time t−1. Upon receipt of measurement z_t at time t, the predicted state is corrected by likelihood factor $p(z_t \mid x_t)$ and re−normalized.

Solving the recursive Bayesian solution is at the core of solving object tracking problems. Different object tracking problems differ in forms of the likelihood function $p(z_t \mid x_t)$ and the transition density $p(x_t \mid x_{t-1})$, and pose different approaches in solving this recursion based on their problem requirements.

3. PARTICLE FILTER FOR OBJECT TRACKING

The particle filter was devised to numerically implement the recursive Bayesian solution which approximates the posterior distribution using a finite set of weighted samples or particles. The particle filter gives discrete approximation to the exact model posterior $p(x_t \mid z_{1:t})$, rather than the optimal solution to an approximate model. It has been introduced by many researchers to solve the estimation problem when the system is nonlinear and non−Gaussian.

The basic idea behind the particle filter is Monte Carlo simulation [7], in which the posterior density is approximated by a set of particles with associated weights. Particle filter are most commonly formulated as sequential importance sampling (SIS) methods. Important density $q(x_t \mid x_{t-1}, z_t)$ can be thought as a well known and easily sampled probability distribution function that is scaled version of $p(x_t \mid z_{1:t})$ with a different scaling factor at each x_t. Thus, SIS involves drawing particles from an importance density, such that particles of the trajectory x_t are obtained by predicting particles for time t from particles in t−1 and current time measurement z_t.

Journal of Theoretical and Applied Information Technology
10th May 2014. Vol. 63 No.1
© 2005 - 2014 JATIT & LLS. All rights reserved·
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

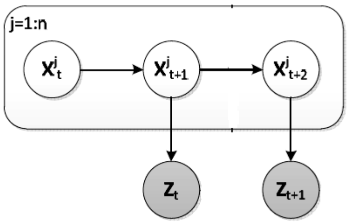


Figure 1: Dynamic Bayesian Network Graph Of Particle Filter

Given n particles $x^1_{t-1}, \dots, x^n_{t-1}$, see graphical model in Figure 1, and their weights $w^1_{t-1}, \dots, w^n_{t-1}$ which represent the posterior distribution at time t−1, it can be calculated weights representing the posterior distribution at time t by:

$$w_t^{(i)} \equiv w_{t-1}^{(i)} \frac{p(x_t^{(i)} \mid x_{t-1}^{(i)})}{q(x_t^{(i)} \mid x_{t-1}^{(i)}, z_t)} p(z_t \mid x_t^{(i)}) \quad i=1 \dots n \tag{5}$$

And the posterior distribution is:

$$p(x_t \mid z_{1:t}) = \sum_1^n w_t^{(i)} \, \delta(x_t - x_t^{(i)}) \tag{6}$$

There are several significant practical problems hidden in the SIS particle filter procedure. First, it is required to determine the likelihood function $p(z_t \mid x_t)$, transition density $p(x_t \mid x_{t-1})$ and importance density $q(x_t \mid x_{t-1}, z_t)$. The likelihood function is based on the observation noise density that is usually assumed to be Gaussian. The transition density is based on the noise in the dynamic transition equation and may be Gaussian, non-Gaussian or completely unknown. Finally, the importance density is usually some known analytical density from which samples can be easily drawn. It must keep in mind, there is re-sampling process in particle filter to generate a new particles set according to particle weights for the next iteration. The resample step decreases the number of the particles with low weight and increases the number of high weight particles.

3.1 Bootstrap Particle Filter

One of the easiest SIS particle filters to implement is the bootstrap particle filter (BPF) introduced in [8]. In the BPF, the transition density is selected as the importance density, that is:

$$q(x_t \mid x_{t-1}, z_t) = p(x_t \mid x_{t-1}) \tag{7}$$

For this choice of importance density, the weight update equation becomes:

$$\tilde{w}_t^{(i)} \equiv w_{t-1}^{(i)} \, p(z_t \mid x_t^{(i)}) \tag{8}$$

The BPF has the distinctive feature that the incremental weights do not depend on the past trajectory of the particles but only on the conditional likelihood of the observation $p(z_t \mid x_t)$. For the BPF, sampling is very straightforward with the state transition equation used to predict new particles and is followed by the resample and move steps. The complete procedure [7] for the BPF is shown in Table 1.

Table 1: The Bootstrap Particle filter

A. Initialize filter	
1. Initialize state vector particles	$x_0^{(i)} \sim q(x_0)$ $i=1, \dots, n$
2. Initialize weights	$w_0^{(i)} = \frac{1}{n}$
B. Sequential importance sampling	
1. Draw new particles	$v_t^{(i)} \sim p(v_t)$ $x_t^{(i)} = f(x_{t-1}^{(i)}) + v_t^{(i)} \quad \forall i$
2. Generate unnormalized importance weights	$\tilde{w}_t^{(i)} \equiv w_{t-1}^{(i)} \, p(z_t \mid x_t^{(i)})$
3. Normalize the weights	$w_t^{(i)} = \tilde{w}_t^{(i)} / \sum \tilde{w}_t^{(i)}$
C. Calculate N_{eff}	$N_{eff} = 1 / \sum \left(\tilde{w}_t^{(i)}\right)^2$
D. If Neff << n	
a. Resample the particles	
b. Calculate the empirical mean	$\hat{x}_t = \frac{1}{n} \sum x_t^{(i)}$
c. Regularize the resampled particles	
d. Time step and return to B.1	$x_t^{(i)} \to x_{t-1}^{(i)}$ $\quad w_t^{(i)} = \frac{1}{n}$
else	
Time step and return to B.1	$x_t^{(i)} \to x_{t-1}^{(i)}$ $w_t^{(i)} = w_{t-1}^{(i)}$
end if	

The noise terms $v_t^{(i)} \sim p(v_t)$ are included in the transition equation for the state vector. Thus, there is also the unstated need for knowledge of the dynamic noise density. Thus to regularize, it can be imposed the transition equation to the resampled particles.

It needs to anticipate the degeneracy caused by migration of the spread of the discrete particle density away to specific dense distribution. A suitable measure of degeneracy for a particular application is the effective sample size N_{eff} that can be estimated from:

Journal of Theoretical and Applied Information Technology
10th May 2014. Vol. 63 No.1
© 2005 - 2014 JATIT & LLS. All rights reserved·
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$$N_{eff} = \frac{1}{\sum_{i=1}^{n} \left(\tilde{w}_t^{(i)}\right)^2} \qquad (9)$$

4. NONRETINOTOPIC PERCEPTION

The key to reverse engineering in visual perception is the understanding of visual information represented and processed in the brain. While it is clear that geometry and visual perception are closely related, very little is known about this relation beyond its early retinotopic association. In visual perception studies, retinotopic refers to the visual process where object in the environment are projected to photo-receptors in the retina in a similar manner as appearance models in a digital image. Nevertheless, a recent study on human vision [3] shows that the representation in higher visual areas of the visual cortex occurs in a nonretinotopic manner: visual perception seems to create dynamic layers for each moving object in the scene. This representation suggests that the appearance of the objects and their positions are marginal independent.

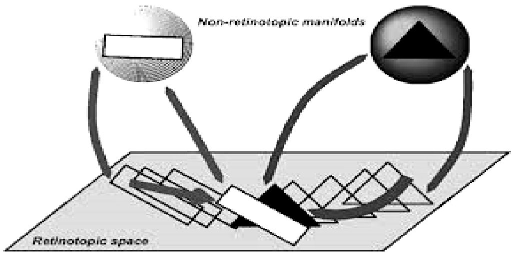


Figure 2: Nonretinopic Concept

In this research, nonretinopic concept is interpreted as the filtering process use past tracking memory about motion dynamics rather than current measurement when quality level of tracking reliability below a threshold. A suitable measure of the tracking quality level for a particular application is sum of current likelihood Qlt that can be estimated from:

$$Qlt = n \sum_{i=1}^{n} p(z_t \mid x_t^{(i)}) \qquad (10)$$

4.1 Formulation of the occlusion problem

Occlusion means that there is something to see, but can't due to some event or some property of your sensor. Occlusion is a fact of visual life. Most of the objects you see are fully or at least partially obscured by other objects.

If a tracking system tracks objects (people, cars, etc) then occlusion occurs if an object is occluded by another object. For example two persons walking past each other, or a car that drives under a bridge. The problem in this case is what the tracking system does when an object disappears and reappears again [1]. In this research, it is implemented visual tracking algorithm based on bootstrap particle filter. Furthermore the algorithm is modified using nonretinotopic concepts, inspired from the way of human visual cortex handles occlusion by constructing nonretinotopic layers. Nonretinopic concept is interpreted using tracking quality level for detecting the tracking estimation of particle filter is not reliable again. Thus when the tracking quality level below a threshold, it is used past tracking memory to track the target.

5. NONRETINOTOPIC PARTICLE FILTER

In this research, we proposed an algorithm based on bootstrap particle filter using a color feature target and enhanced by nonretinotopic concept. A specific probabilistic graphical model in Figure 3 is used for defining the proposed technique.

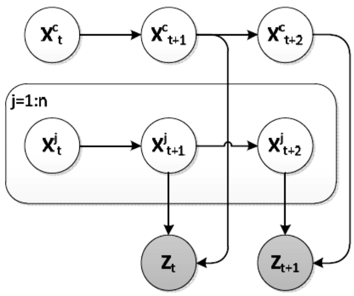


Figure 3: Bayesian Network Of Nonretinotopic Particle Filter

In nonretinotopic particle filter, BPF is modified by adding the tracking estimation quality procedure after resample the particles and using past tracking memory that is the target object x_t^C represented by empirical mean $\hat{x}_t$. The modification procedure is shown in Table 2.

Table 2: The modification in nonretinotopic particle filter

D. If Neff << n	
a. Resample the particles	
If Qlt > threshold	$Qlt = n \sum_{i=1}^{n} p(z_t \mid x_t^{(i)})$
b. Calculate the empirical mean	$\hat{x}_t = \frac{1}{n} \sum x_t^{(i)}$
c. Regularize the resampled particles	
else	
d. Calculate nonretinotopic update	$x_t^{(i)} = f(x_{t-1}^{(i)})$
e. Spread the	$\sigma_t = 3.\sigma_{t-1}$

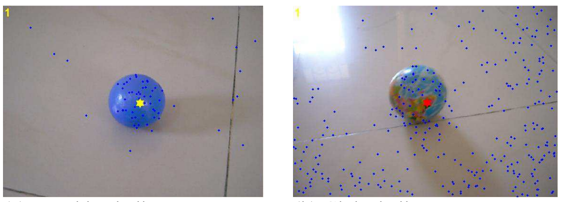
Journal of Theoretical and Applied Information Technology
10th May 2014. Vol. 63 No.1
© 2005 - 2014 JATIT & LLS. All rights reserved·
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

particles on scene based on velocity standard deviation	
end if	
f. Time step and return to B.1	$x_t^{(i)} \rightarrow x_{t-1}^{(i)}$ $w_t^{(i)} = \frac{1}{n}$
else	
Time step and return to B.1	$x_t^{(i)} \rightarrow x_{t-1}^{(i)}$
end if	$w_t^{(i)} = w_{t-1}^{(i)}$

As a Bayesian estimator, nonretinotopic particle filter has two main steps: prediction and update. Prediction is done by propagating the particles based on the transition model. The update step is done by measuring the weight of each particles based on the observation model. The implementation of nonretinotopic particle filter can be described as follows.

1. Particle initialization.

In this research, the initialization of the particles is done by putting the particles randomly on entire scene depend on video resolution. For object target is used blue color feature in RGB format (0, 0, 255). Furthermore it is used two blue objects in experiment that is: pure blue ball and globe ball. In this initialization approach, it is used tracking quality level to determine the beginning of object tracking, when the level is more than a threshold. It can be seen on Figure 4, that pure blue ball can start to track since time step 1, indicated by yellow star.



(a) Pure blue ball (b) Globe ball

Figure 4: Initialization Based On Random Particles

2. Prediction: Transition model.

In this research, the motion of the object is considered as the discrete time 2-dimensional (2D) motion with constant velocity assumption. The state vector at a time step t is denoted by $\vec{x}_t$, including horizontal position, vertical position, horizontal velocity, vertical velocity of each particle. The noise terms $v_t^{(i)} \sim p(v_t)$ are Gaussian noise included in the transition equation for the state vector. The noise terms provide the system with a diversity of hypotheses. Thus, each component of the particles is predicted by propagating past state vector according to the transition model. For this purpose, the equations system of transition model is described by:

$$\begin{bmatrix} x_t \\ y_t \\ \dot{x}_t \\ \dot{y}_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_{t-1} \\ y_{t-1} \\ \dot{x}_{t-1} \\ \dot{y}_{t-1} \end{bmatrix} + \begin{bmatrix} v_x \\ v_y \\ v_{\dot{x}} \\ v_{\dot{y}} \end{bmatrix} \tag{11}$$

Furthermore, when the tracking quality level below a threshold (Qlt < threshold), it is used past tracking memory to track the target based on new dynamic transition model. The motion of the target can be modeled using a coordinated turn model [9] of the form:

$$\begin{bmatrix} x_t \\ y_t \\ \dot{x}_t \\ \dot{y}_t \end{bmatrix} = \begin{bmatrix} 1 & 0 & \frac{\sin\omega}{\omega} & -\frac{1-\cos\omega}{\omega} \\ 0 & 1 & \frac{1-\cos\omega}{\omega} & \frac{\sin\omega}{\omega} \\ 0 & 0 & \cos\omega & -\sin\omega \\ 0 & 0 & \sin\omega & \cos\omega \end{bmatrix} \begin{bmatrix} x_{t-1} \\ y_{t-1} \\ \dot{x}_{t-1} \\ \dot{y}_{t-1} \end{bmatrix} + \begin{bmatrix} v_x \\ v_y \\ v_{\dot{x}} \\ v_{\dot{y}} \end{bmatrix} \tag{12}$$

where, $\omega \in (-\pi, \pi)$ in rads/s is rate of turn which can be adjusted depend on the target motions. In the limiting case of the rate of turn parameter $\omega \rightarrow 0$, the coordinated turn model simplifies to equation (11).

3. Update: Observation model

The observation model is used to measure the observation likelihood of the particles. The likelihood function is based on the observation noise density and is assumed to be Gaussian. For this purpose, the likelihood function using deviation from target d is described by:

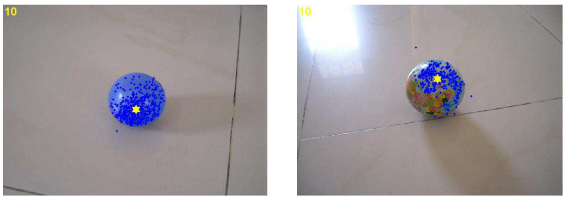
$$p(z_t \mid x_t^{(i)}) = \frac{1}{\sqrt{2\pi\sigma}} \exp^{\left(-\frac{d^2}{2\sigma^2}\right)} \tag{13}$$

In this research, the observation model is made based on color information of the target obtained by building the color histogram in the RGB color space. Moreover, it is used blue color feature in RGB format (0, 0, 255) as object target. Thus the deviation d is defined using Euclidean distance as:

$$d = \sqrt{R^2 + G^2 + (B-255)^2} \tag{14}$$

To maintain a consistent particle, the new importance weights are set by measuring the likelihood of each particle based on the observation model. Figure 5 shows examples of object target at frame #10.

Journal of Theoretical and Applied Information Technology
10th May 2014. Vol. 63 No.1
© 2005 - 2014 JATIT & LLS. All rights reserved·
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195



(a) Pure blue ball (b) Globe ball

Figure 5: Examples Of Object Target At Frame #10

4. Resample the particles

The resample step is performed to produce new particles based on the current particles weight. During the resample step, particles with high weight possibly will be chosen several times generating identical copies, while others with relatively low weights may possibly be ignored and deleted. The resample step [7] can be done in the following steps:

a. Generate n random numbers that is uniformly distributed on [0,1] that is $u_j \sim U(0,1) \quad j = 1 \ldots n$
b. Calculate the cumulative probability of the normalized particles weight. The result is intervals $w_t^{(i)} \le x < w_t^{(i+1)}$ where $i=1 \ldots n$
c. Find the interval where $w_t^{(i)} \le u_j < w_t^{(i+1)}$ and set the new particle $x_t^{(j)} = x_t^{(i)}$

6. EXPERIMENTAL RESULTS

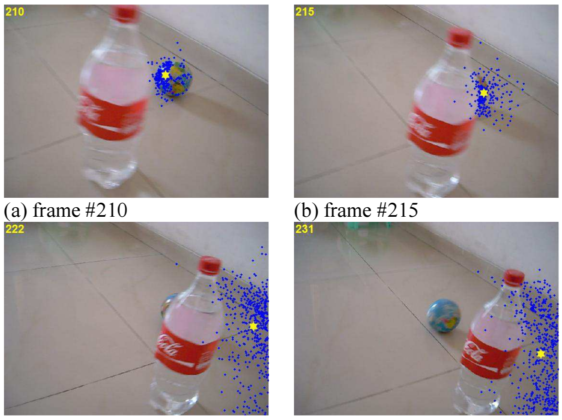
In order to evaluate the proposed method, it is done the experiments using a video camera to track the objects. The experiments are implemented on Intel i3 2.53 [GHz] CPU and 2 [GB] RAM. The resolution of each frame is 552×402 [pixels] image. In each experimental result, the blue dots represent the particles, the yellow star represents object target from generic particle filter, calculated from the mean state of the particles position and the red star represents the object target from nonretinotopic particle filter.

The experiments are done using 1000 particles and in three challenges that is occlusions in general and with motion and illumination in particular. The initial position of the target object is assumed unknown. For object target is used blue color feature in RGB format (0, 0, 255). Furthermore it is used two blue objects in experiment that is: pure blue ball and globe ball. As default, tracking quality threshold is set equal to 1 except in the illumination challenge.

6.1 Object tracking with occlusion

In this experiment, it is compared generic bootstrap particle filter with nonretinotopic particle filter when the target object is fully and partially obscured by other objects. While the target object is pure blue ball, there is no different performance between two algorithms. The two algorithms can track the pure blue ball very well.

On the other hand, there is very interesting result for globe ball target. Figure 6 shows the performance of generic bootstrap particle filter in handling full occlusion (frame #210 – frame #231) using globe ball target. As shown in that figure, the algorithm fails to track the target object and traps in local area.

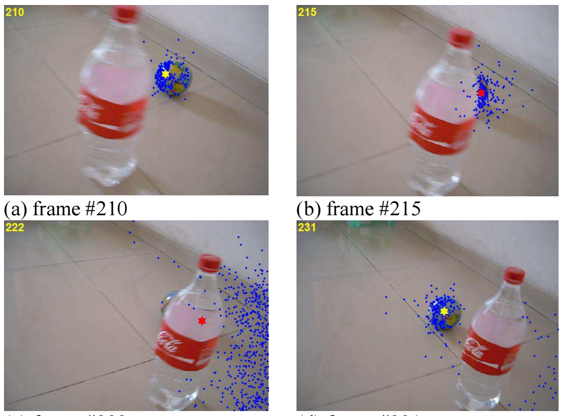


(a) frame #210 (b) frame #215

(c) frame #222 (d) frame #231

Figure 6: Generic Particle Filter In Handling Occlusion Challenge

Figure 8 shows the performance of nonretinotopic particle filter in handling full occlusion (frame #210 – frame #231) using globe ball target. As shown in that figure, the algorithm can track successfully the target object although the partial and full occlusion occurs.



(a) frame #210 (b) frame #215

(c) frame #222 (d) frame #231

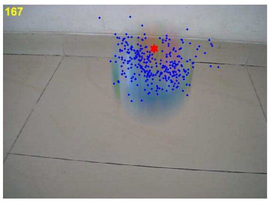
Figure 7: Nonretinotopic Particle Filter In Handling Occlusion Challenge

6.2 Object tracking with different motions

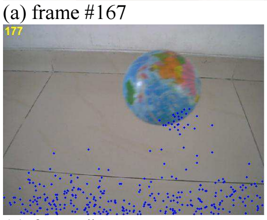
In this experiment, it is observed the algorithm performance when the target object performs vertical and horizontal motions. For the horizontal motions, the tracking algorithm can track the globe ball very well. However while the target performs

Journal of Theoretical and Applied Information Technology
10th May 2014. Vol. 63 No.1
© 2005 - 2014 JATIT & LLS. All rights reserved·
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

vertical motions, there is interesting phenomena that is the particles sometime only follow the target object poorly. As shown in figure 10, the particles in frame #167 – frame #180 fail to follow the target object and have to spread in searching the target object.


(a) frame #167


(b) frame #172


(c) frame #177

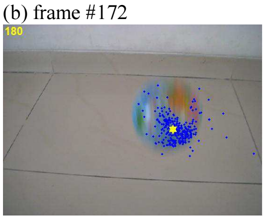
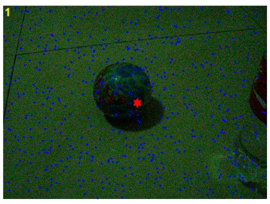

(d) frame #180

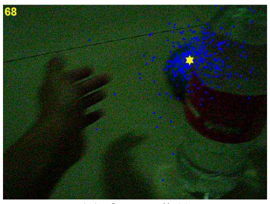
Figure 8: Nonretinotopic Particle Filter In Handling Vertical Motions

6.3 Object tracking with different illumination

In this experiment, it is observed the algorithm performance when the object tracking is performed in different illumination environment that is outdoor, indoor and dark room. In outdoor and indoor environment, there is no out of ordinary occurrence. However, in dark room there is something remarkable that is the algorithm cannot track the globe ball target at all using default tracking quality threshold. When this threshold is decreased to 0.1, the tracking algorithm starts to track the target object in usual manner. Overall, the performance of the tracking object in dark room is decreased considerably. This illumination challenge may be treated using image processing such as Histogram equalization. As presented in Figure 11, the particles in frame #1 – frame #74 tend to spread around the target object in order to follow its motions.


(a) frame #1


(b) frame #57


(c) frame #68


(d) frame #74

Figure 9: Nonretinotopic Particle Filter In Dark Environment

7. CONCLUSIONS

This paper presented a method to track the moving object employing bootstrap particle filter based on color information. Furthermore, the algorithm is modified using nonretinotopic concepts, inspired from the way of human visual cortex handles occlusion by constructing nonretinotopic layers. There are three main conclusions: (i) the performance of the object tracking algorithm in handling occlusion can be improved using nonretinotopic concept, (ii) dynamic model is crucial for object tracking, especially when the target object experienced occlusion and maneuver motions, (iii) the dependency of the tracker performance on the accuracy of tracking quality threshold when facing illumination challenge.

The algorithm is still restricted to track single object and will extend to track multiple object and will enhance by creating the advanced dynamic model. These are remaining for our future works.

REFRENCES:

[1] A.O. Ercan, A. El Gamal, and L.J. Guibas, "Object Tracking in the Presence of Occlusions via a Camera Network," in *6th International Symposium on Information Processing in Sensor Networks*, 2007, pp. 509-518.

[2] Budi Sugandi, Hyoungseop Kim, Joo Kooi Tan, and Seiji Ishikawa, "Object Tracking Based on Color Information Employing Particle Filter Algorithm," in *Object Tracking*, Hanna Goszczynska, Ed.: Intech, 2011, ch. 4, pp. 69-88.

[3] H. Ogmen and M. Herzog, "The Geometry of Visual Perception: Retinotopic and Nonretinotopic Representations in the Human Visual System," *Proceedings of the IEEE*, vol. 98, no. 3, pp. 479-492, March 2010.

[4] Gijs Plomp, Manuel R. Mercier, Thomas U. Otto, Olaf Blanke, and Michael H. Herzog, "Non-retinotopic feature integration decreases response-locked brain activity as revealed by electrical neuroimaging," *NeuroImage*, vol. 48, no. 2, pp. 405-414, 2009.

© 2005 - 2014 JATIT & LLS. All rights reserved·
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[5] S. Challa, M. R. Morelande, D. Mušicki, and R. J. Evans, *Fundamentals of Object Tracking*.: Cambridge University Press, 2011.

[6] L. Marcenaro, C. S. Regazzoni, and M. Soto, "Dynamic Bayesian multi-target tracking for behavior and interaction detection," in *Effective Surveillance for Homeland Security: Balancing Technology and Social Issues*, Francesco Flammin, Roberto Setola, and Giorgio Franceschetti, Eds.: CRC Press/Taylor-Francis, 2013, pp. 489-510.

[7] A. J. Haug, *Bayesian Estimation and Tracking: A Practical Guide*.: Wiley, 2012.

[8] Gordon N, Salmond D, and Smith AF, "Novel approach to nonlinear/non−Gaussian Bayesian state estimation," *IEEE Proc. F. Radar Signal Process*, no. 140, pp. 107–113, 1993.

[9] Christopher Nemeth, Paul Fearnhead, Lyudmila Mihaylova, and Dave Vorley, "Particle learning methods for state and parameter estimation ," in *Data Fusion & Target Tracking Conference (DF&TT 2012): Algorithms & Applications, 9th IET*, 2012, pp. 1-6.