Vol. 4, No. 3 Mar 2013 ISSN 2079-8407
Journal of Emerging Trends in Computing and Information Sciences


http://www.cisjournal.org

# BFO vs. BSO for Video Object Tracking Using Particle Filter (PF)

[1] Mohammed Alhanjouri, [2] Ahmed Al Ostaz
[1] Associate Professor, Department of Computer Engineering, Islamic University of Gaza, Palestine
[2] Postgraduate Student, Department of Electrical Engineering, Islamic University of Gaza, Palestine
[1] mhanjouri@iugaza.edu.ps, [2] aostaz@gmail.com

## ABSTRACT

In this paper, we introduced a new algorithm for Video tracking, which is the process of locating a moving object (or multiple objects) over time using a camera. A new particle filter based on bacteria foraging optimization (PF-BFO) is introduced in field of video object tracking. This paper reviews particle filter and using it for tracking. Particle Swarm Optimization (PSO) is also described. Moreover, using the combination of PSO with PF (PF-PSO) in video object tracking is reviewed. Bacterial Foraging Optimization (BFO) is a novel heuristic algorithm inspired from forging behavior of E. coli. After analysis of optimization mechanism, a series of measures are taken to improve the classic BFO by using Particle filter. The PSO is a meta-heuristic which is also inspired from insects' life as ACO. Even both methods use a population of entities. The comparison between PF-BFO and PF-PSO for video object tracking is presented in this work. The results show that PF is strong tool in tracking field. On the other hand, PF-BFO method presents outstanding performance versus PF-PSO.

**Keywords:** *Video object tracking, Particle filter, Bacteria foraging optimization, Particle swarm optimization.*

## 1. INTRODUCTION

The applications of object tracking are heavily used in computer vision. However, there are a number of challenges. Although many substantial researches have been done to tackles the challenges, developing a robust and efficient tracking algorithm still unsolved because of hardship in tracking problem.

Recently, Particle filters have been extensively used in tracking field. They proved to be a robust method of tracking due to their ability of solving non-Gaussian and non-linear problems. Video object tracking through using PF suffers the same problems that PF do: degeneracy phenomenon and sample impoverishment.

The degeneracy phenomenon, where after a few iterations, all but one particle will have negligible weight, is an undesirable effect in particle filter. To reducing its effect, to a great number of particles is used. This will increase the computational cost. In order to reduce the effects of degeneracy, many particle filters introduce a re-sampling procedure whenever a significant degeneracy is observed. The basic idea of re-sampling is to eliminate particles that have small weights and to concentrate on particles with large weights. But the re-sampling step introduces other practical problems, such as the problem of sample impoverishment.

Sample impoverishment occurs when the likelihood is very narrow or the likelihood distribution function lies at the tail of prior distribution. This sample impoverishment can be solved through enlarging the sample set to cover the whole state space and to ensure estimation successfully. Therefore, the computation will be negatively affected.

In this paper, the researchers use new technique, particle filter based on BFO in video object tracking, to reduce impoverishment and degeneracy problem. The comparison between PF-BFO and PF-PSO in video object tracking shows the advantages of this new technique.

This paper is organized as follows: Section 2 states related work. Section 3 is about the particle filter algorithm and using it in tracking. Section 4 shows generic PSO. In Section 5 the researchers review using PF-PSO in tracking of video object. In section 6 describes BFO. Section 7 shows how to use Particle Filter Algorithm based on BFO in video object tracking. In section8 the experiment results is shown. Finally, Section 9 includes the conclusions and discusses the issues for future research.

## 2. RELATED WORK

To reduce degeneracy and impoverishment problem, many approaches are proposed for example:

- The Mean-shift algorithm is added to the particle filter in object tracking [1] .the mean shift improves the weights of particles before resample. That overcomes the degeneracy problem of conventional particle filters and requires less computational cost.
- PF is combined with PSO [2]. PSO improves the way of resample particle to deal with the problem of sample impoverishment. Using (PF-PSO) in video object tracking [3, 4] shows the strength of PF-PSO.
- Improved particle filter based on genetic algorithm (GA) is proposed in [5]. This paper introduces genetic Monte Carlo sampling method, and then uses it in the re-sampling step of particle filter with the basic idea of solving particle degeneration.
- Combining particle filter with ant colony optimization is used in video object tracking [6]. That reduces the size of sample set and effects of the problems of PF.

Journal of Emerging Trends in Computing and Information Sciences


http://www.cisjournal.org

## 3. VIDEO OBJECT TRACKING USING PARTICLE FILTER

### A. Particle Filter

PF is a Bayes estimation algorithm based on Monte Carlo method. It performs the posterior probability density function via a number of weighted particles and eliminates particles that have small weights and concentrates on particles with large weights using resample .The details of algorithm is shown below [7]:

(1) Initialization: k=0
For i=0……… $N_s$
Draw the states $X_0^i$ from the P( $X_0$ )
End for

(2) For k= 1, 2
(a) For i=0……… $N_s$

Draw $X_k^i \sim q(X_k^i | X_{k-1}^i, Z_k)$ (1)

Assign the particle a weight $W_k^i$ according to

$$W_k^i \propto W_{k-1}^i \frac{P(Z_k | X_k^i)\, P(X_k^i | X_{k-1}^i)}{q(X_k^i | X_{k-1}^i, Z_k)}$$

(2)

End for

(b) For i=0……… $N_s$

Normalize the weights $W_k^i = W_k^i / \sum_{j=0}^{N_s} W_k^j$ (3)
End for.

(c) Resample:

Multiply/Suppress samples $x_{0:k}^{(i)}$ with high/low $W_k^i$ obtain $N_s$ random samples $x_{0:k}^{(i)}$ approximately distributed according to $P(X_{0:k} | Z_{1:k})$

For i=0……… $N_s$ $W_k^i = 1/N_s$ (4)
End for
End for

### B. Video Object Tracking Using PF:

To achieve video object tracking by PF [1, 3, 4, 5, 6, 8, 9, and 10], we do the following:

1. Applying PF algorithm to each frame of the video in sequence.
2. Sampling the particles of the first frame in pixels and organizing them in set S.
3. Predicting set S in every frame using Randomly Gaussian Noise U.

$$S_t = AS_{t-1} + U_{t-1} \quad (5)$$

4. Using the value of the pixel for weighting the particle in comparison with previously taken value of the tracked video object.
5. Re-sampling the particles according to their new weights, and then estimating the location of the video object.

$$\hat{X} = \frac{\sum_{i=1}^{N_s} X_k^i}{N_s} \quad (6)$$

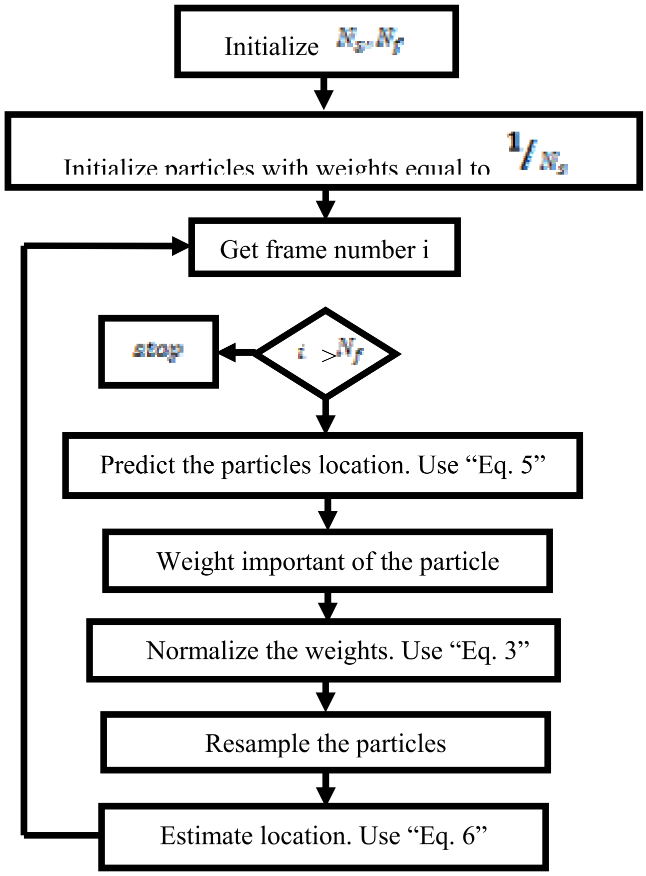



**Fig 1:** flow chart of video object tracking using PF
$N_s$ = Number of particle. $N_f$ = Number of video frame.

### C. Weight Technique

To reduce the difficulty of tracking as the result of changing in elimination, different types of cue are used in weighting particle such as using histogram color, histogram edge [8] , texture [9] and histogram of spatial color [10] . In this paper simple weighing cues is used to show the strength of combining particle filter with optimization algorithms. Moreover, two cue for weighing are used:

- Histogram color of the particle -pixel value- Hi is compared with wanted histogram color pixel Htarget:

$$D_H = H_k^i - H_{target} \quad (7)$$

Vol. 4, No. 3 Mar 2013 ISSN 2079-8407
Journal of Emerging Trends in Computing and Information Sciences

http://www.cisjournal.org

$$W_H^i = \frac{1}{\sqrt{2\pi\sigma_{color}}} e^{\frac{-D_H^2}{2\sigma_{color}^2}} \quad (8)$$

- The position of the particle Xi is compared with the best previous position Xtarget which equals previous location of the tracked video object.

$$D_p = X_k^i - X_{target} \quad (9)$$

$$W_p^i = e^{\frac{-D_p^2}{2\sigma_{postion}^2}} \quad (10)$$

The weight of particle is calculated in the paper according equation:

$$W_k^i = W_H^i * W_p^i \quad (11)$$

## 4. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization is a swarm intelligence technique which was proposed by Kennedy and Eberhart in1995 [11]. The PSO is developed based on the following model [12]:

- When one bird locates a target or food (or maximum of the objective function),it instantaneously transmits the information to all other birds.
- All other birds gravitate to the target or food (or maximum of the objective function), but not directly.
- There is a component of each bird's own independent thinking as well as its past memory.

Thus the model simulates a random search in the design space for the maximum value of the objective function. As such, gradually over much iteration, the birds go to the target (or maximum of the objective function).

The PSO procedure can be implemented through the following steps:

1. Assume the size of the swarm (number of particles) is N.
2. Generate the initial population of X .randomly as X1, X2. . . XN (positions of particle).
3. Find the velocities of particles. All particles will be moving to the optimal point with a velocity. Initially, all particle velocities are assumed to be zero.
4. In the $i^{th}$ iteration, find the following two important parameters used by atypical particle j :

   (a) The historical best value of Xj (i) (coordinates of $j^{th}$ particle in the cur-rent iteration i ) , Pbest,j , with the highest value of the objective function, f[Xj(i)], encountered by particle j in all the previous iterations.

   The historical best value of Xj (i) (coordinates of all particles up to that iteration), Gbest , with the highest value of the objective function f [Xj(i)],encountered in all the previous iterations by any of the N particles.

   (b) Find the velocity of particle j in the i Th iteration as follows:

$$V_j(i)=V_j(i-1)+C_1R_1*(P_{best,j}-X_j(i-1))+C_2R_2*[Gbest-X_j(i-1)]$$

$$j = 1, 2. . . N \quad (12)$$

   (c) Find the position or coordinate of the j th particle in i th iteration as

$$X_j\ (i) = X_j\ (i-1) + V_j\ (i) \qquad j = 1, 2, . . . , N \quad (13)$$

5. Check the convergence of the current solution. If the positions of all particles converge to the same set of values, the method is assumed to have converged. If the convergence criterion is not satisfied, step 4 is repeated by updating the iteration number as i = i + 1, and by computing the new values of $\mathbf{P}_{\mathbf{best,j}}$ and $\mathbf{G}_{\mathbf{best}}$. The iterative process is continued until all particles converge to the same optimum solution.

## 5. VIDEO OBJECT TRACKING USING PARTICLE FILTER BASED ON PSO

Combining particle filter with PSO is proposed in [2]. This combination is used in video object tracking [4]. In this paper the same algorithm is performed, but the number of PSO iteration ($N_i$ ) is controlled. The algorithm is shown in flow chart in figure (2):

Vol. 4, No. 3 Mar 2013 ISSN 2079-8407
Journal of Emerging Trends in Computing and Information Sciences

http://www.cisjournal.org

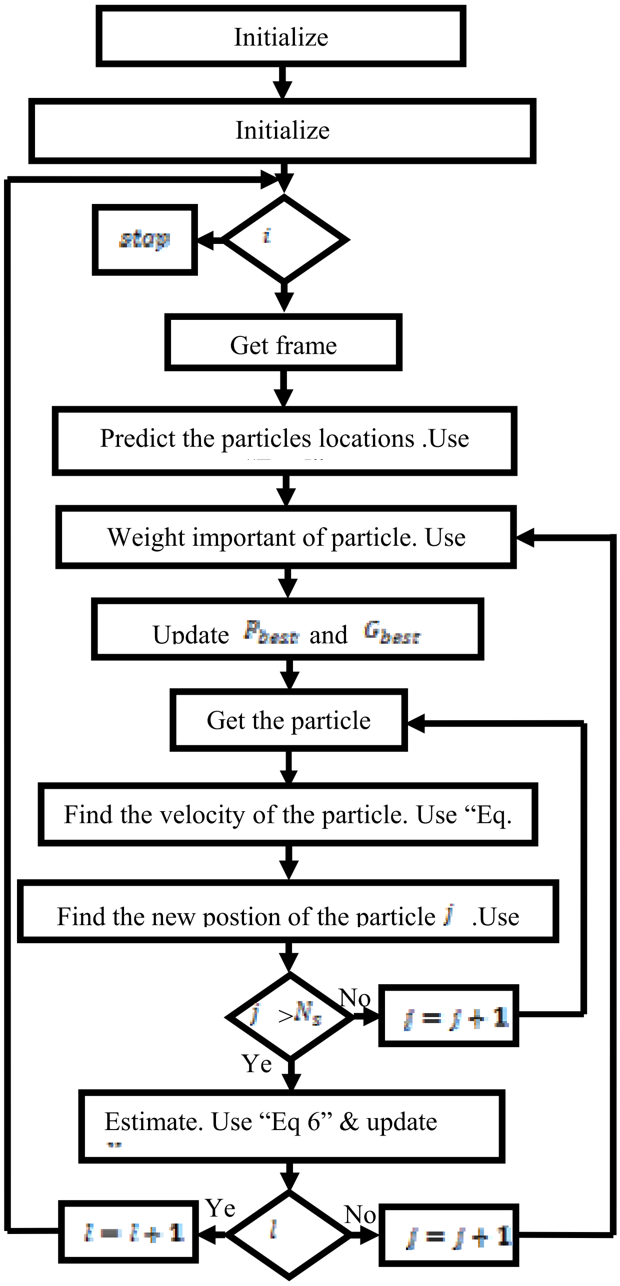



**Fig 2:** flow chart of Particle Swarm Optimization Algorithm

$N_s$ = the number of the particles.

$N_f$ = the number of the frames of video.

$N_i$ = the number of iteration of PSO

## 6. BACTERIAL FORAGING OPTIMIZATION

Like other swarm intelligence algorithms, BFOA is based on social and cooperative behaviors found in nature. In fact, the way Bacteria look for regions of high levels of nutrients can be seen as an optimization process. The bacteria foraging strategy can be explained by four processes [16]:

**a. Chemotaxis:**

This process simulates the movement of an E.colicell through swimming and tumbling via flagella. Biologically an E.coli bacterium can move in two different ways. It can swim for a period of time in the same direction or it may tumble, and alternate between these two modes of operation for the entire lifetime

**b. Swarming [13]:**

For the bacteria to reach at the richest food location, it is desired that the optimum bacterium till a point of time in the search period should try to attract other bacteria so that together they converge at the desired location more rapidly. To achieve this, a penalty function based upon the relative distances of each bacterium from the fittest bacterium till that search duration, is added to the original cost function. Finally, when all the bacteria have merged into the solution point, this penalty function becomes zero.

**c. Reproduction :**

The least healthy bacteria eventually die while each of the healthier bacteria asexually split into two bacteria, which are then placed in the same location. This keeps the swarm size constant.

**d. Elimination and dispersal :**

Gradual or sudden changes in the local environment where a bacterium population lives may occur due to various reasons e.g. a significant local rise of temperature may kill a group of bacteria that are currently in a region with a high concentration of nutrient gradients. Events can take place in such a fashion that all the bacteria in a region are killed or a group is dispersed into a new location.

The BFO algorithm is summarized below:

1. Initialize input parameter:
   $S_p$: Total number of bacteria in the population.
   $N_c$: The number of chemotactic steps.
   $N_{re}$: The number of reproduction steps.
   $N_s$: The length of swim
   $N_{ed}$: The number of elimination-dispersal events.
   $P_{ed}$: Elimination-dispersal probability.
   $C(i)$: The size of the step taken in the random direction specified by the tumble.

2. Create random initial swarm bacteria θi (j, k, l) and initialize their fitness J health

3. For i =1, 2 … Ned
   For $j$ =1, 2 … $N_{re}$
   For $k$ =1, 2 … $N_c$
   For $l$ =1, 2 … $S_p$

Vol. 4, No. 3 Mar 2013 ISSN 2079-8407
Journal of Emerging Trends in Computing and Information Sciences



Perform chemotaxis step:

1) Compute fitness function, $J$ $(i, j, k, l)$.
2) Perform tumble (indicate direction of step)
3) Swim with suitable $C$ $(i)$ until improve fitness nor arrive the length of swim $N_s$ .

End for
End for

The $S$ bacteria with the highest $J$ health values die and the remaining $S$ bacteria with the best values split
End for

Perform the reproduction step by eliminating _dispersal step for all bacteria $\theta_i$ **(j, k, l)** with probability $0<P_{ed}<1$.
End for

The detailed mathematical derivations as well as theoretical aspect of this new concept are presented in [14, 15].

## 7. VIDEO OBJECT TRACKING USING PARTICLE FILTER BASED ON BFO

Combining PF with BFO use bacteria as particles, their health as weights and bacterial foraging strategy are achieved as shown below in flowchart in figure (3).

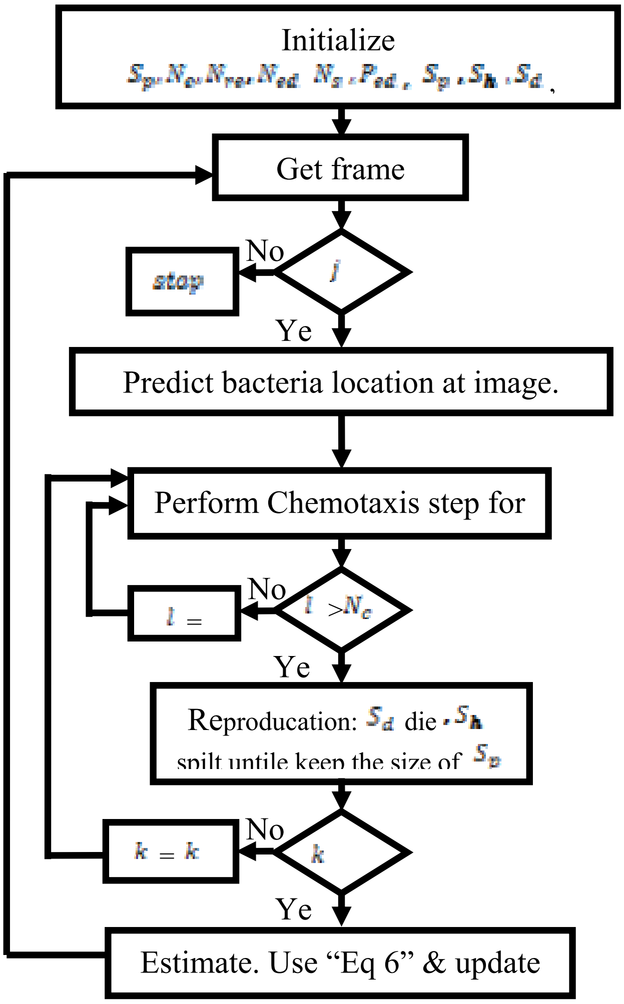



**Fig 3:** Video Object Tracking Using Particle Filter Based on BFO

**a. Elimination and dispersal :**

We consider video frames elimination and dispersal events. Each frame has new measurements and new predictions about the particles.

**b. Chemotaxis Step:**

We use Chemotaxis step to improve the weights of the particles -health of bacteria - before re-sampling. Our ability to change the number of Chemotaxis steps and the length of swim enables us to control the improvement of weight more than mean shift does [1].

**c. Swarming:**

Since swarming provides social behavior between bacteria, it improves the Wight of particle.

**d. Reproduction:**

Reproduction is used to resample particle. Consider $S_d$, low weighted particles, dead bacteria and $S_h$, high weighted particles, bacteria alive and splitting. $S_d$ does not equal $S_h$, and $S_h$ is able to split more than a time to keep the swarm size constant. The ability to re-product more than once in one iteration and to choose the number of $S_h$ ***and*** $S_d$ provides high control for re-sampling step in particle filter.

## 8. EXPERIMENTS AND RESULT

Comparison between PF-PSO and PF-BFO for object tracking is made. The color of the skin of the little child in figure (4) is tracked in sample video which is taken by a cheap camera and has strong Wight noise, high variance elimination and high similarity between colors.

**Fig 4:** The little child that will be an object to track.

In contrast with Simple Approach which proposes solving the problem of degeneracy and impoverishment through using a great number of particles, the researchers propose the use of a less number of particles for tracking. The researchers believe that is a means for measuring the strength of tracking technique. In addition, they use color

Vol. 4, No. 3 Mar 2013 ISSN 2079-8407
Journal of Emerging Trends in Computing and Information Sciences

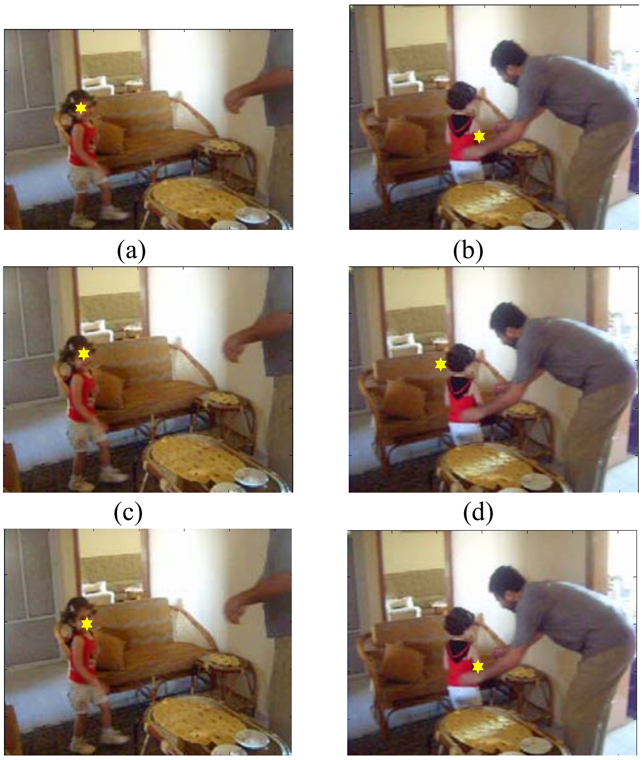
http://www.cisjournal.org

standard deviation (3) as a measurement tool which introduces less variance more accuracy.

Firstly, PF-PSO is used with one iteration and PF-PFO is used with following parameter: Nr=1, Nc=1and Ns=1, we have the results shown in table 1 and figure (5)

**Table 1:** Results of PF-PFO Algorithm with parameters: Nr=1, Nc=1and Ns=1

| PF TYPE | Min number of particles hold tracking | Color Standard Deviation |
|---|---|---|
| PF_PSO | 88 | 7 |
| PF_BFO | 40 | 5 |



(a) (b) (c) (d) (e) (f)

**Fig 5:** Results of PF-PSO & PF-BFO

Figure (5) (a) and (b) show that the PF-PSO can track the object the frames 30 and 65 with 88 particles and color standard variation 7. Although PF-PSO with 87 particles can track the object in frame 30 as shown in figure (5)(c), it cannot track in frame 65 as shown in figure (5)(d)

Figure (5) (e) and (f) show that the PF-BFO can track the object in frame 30 and 65 with 40 particles and color standard variation 7.

However Figure(6)(a) shows that the PF-PSO can hold the tracking in frame 100 with 88 particles and color standard variation 7, it can't track with 88 particles and color standard variation 6 as Figure(6)(b) shows.

**Fig 6:** Standard variation effects on tracking results by using PF-PSO.

Addition to Figure (7)(a) shows the PF-BFO can track the object in frame 130 with 40 particles and color standard variation 6, it can match with 40 particles and color standard variation 5 as Figure(7)(b) shows.

**Fig 7:** PF-BFO results with different Standard variation.

Secondly, to improve tracking we increase the iteration of PF-PSO and PF-BFO. The number of iteration needed to hold tracking at ***N*** particle is used to measure the strength of tracking. It is believed that less iteration more robust tracking. The number of iteration of PF-BFO equal to ***Nr * Nc * Ns***. Results is shown in table (2), figure (8) and figure (9)

**Table 2:** Comparison between PF_PSO and PF-BFO

| Number of iteration of PF type | Number of particles | | | | | | |
|---|---|---|---|---|---|---|---|
| | 70 | 60 | 50 | 40 | 30 | 20 | 10 |
| PF_PSO iteration | 10 | 15 | 30 | NA | NA | NA | NA |
| PF-BFO iteration | 1 | 1 | 1 | 1 | 3 | 9 | 9 |

NA means cannot track

**Fig 8:** Number of iteration effects on PF-PSO

Although , PSO can hold tracking with 50 particles at 30 iterations in frame 60 as shown in figure(8)(a) ,it can't hold tracking with 40 particles as shown in figure(8)(b).

In addition ,figure(9)(a) shows that PF-BFO hold tracking with 20 particles at 9 iterations in frame 60, it can hold tracking with 10 particles at the same iteration as shown in figure(9)(b).

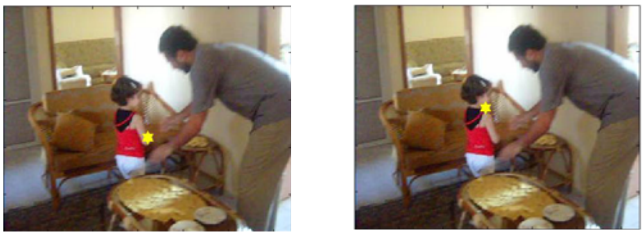


**Fig 9:** Number of iteration effects on PF-BFO

Thirdly, the Comparison provides another advantage to PF-BFO that is the stability. In each prediction stage, the particles move using Randomly Gaussian Noise which affects the stability of tracking technique .Low stability means that through using the same number of particles and color standard division, tracking technique may succeed or not. This phenomenon is noticed at PF-PSO, but it is not noticed at PF-BFO.

With the same number of particles and the same frame, PF-PSO can hold tracking in figure (10) (a), but it cannot figure (10) (b).

**Fig 10:** Instability of PF-PSO

## 9. CONCLUSIONS

In this paper we provide unprecedented method, PF-BFO, in video object tracking. The results show that the new particle filter is more accurate and stable tracking. It solves both degeneracy phenomenon and impoverishment problem. The new method has the advantages of both adding mean shift to PF and improving resample method of PF. However, applying new method in real time video tracking needs processor that has high velocity.

Further studies:

- Using advance technique in weighting particle will make PF-BFO tracking more robust.
- Using synchronous Bacteria Forging optimization instead of BFO for faster. tracking

## REFERENCES

[1] Bai and Weiming Liu, "Improved Object Tracking with Particle Filter and Mean Shift" , Proceedings of the IEEE, International Conference on Automation and Logistics , August 18 - 21, 2007, Jinan, China

[2] Gongyuan Zhang, Yongmei Cheng, Feng Yang, Quan Pan, "Particle Filter Based on PSO", International Conference on Intelligent Computation Technology and Automation, 20-22 Oct. 2008.

[3] Howida A. Abd El-Halym, Imbaby I. Mahmoud, A. AbdelTawab and S. E.-D. Habib, "Particle Filter versus Particle Swarm Optimization for Object Tracking" , Th 13 International Conference on AEROSPACE SCIENCES & AVIATION TECHNOLOGY , May 26 – 28, 2009.

[4] Zhou Hao Xuejie Zhang Haiyan Li Jidong Li, "Video Object Tracking Based on Swarm Optimized Particle Filter", International Conference on Industrial Mechatronics and Automation (ICIMA), May 30-31 2010

[5] Long Ye , Jingling Wang , Chuanzhen Li , Hui Wang and Qin Zhang, "A Novel Particle Filtering Framework Using Genetic Monte Carlo Sampling" , International Conference on Management and Service Science, Sept 20-22 2009.

[6] Zhou Hao Xuejie Zhang Pengfei Yu Haiyan Li, "Video Object Tracing Based on Particle Filter with Ant Colony Optimization", International Conference on Advanced Computer Control (ICACC), March 27-29 2010 .

[7] M. Arulampalam, S. Maskell, N. Gordon and T. Clapp, "A turorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking,"IEEE Trans. On Signal Proc. 50 (2), pp. 174-188, 2002.

[8] Ke-Yan Liu, Shan-Qing Li, Liang Tang, Lei Wang and Wei Liu, "fast face tracking using parallel particle filter algorithm" , IEEE International Conference on Multimedia and Expo, June 28 2009- July 3 2009.

[9] RuiQing Chen , ZhaoHui Zhang, HanQing Lu , HuiQing Cui , YuKun Yan, "Particle filter based object tracking with color and texture information fusion" , International Symposium on Intelligence Information Processing and Trusted Computing (IPTC), 2010 pp. 626 – 630.

[10] Jiaqing Ma, Chongzhao Han and Yuxi Chen, "Efficient Visual Tracking Using Particle Filter", 10th International Conference on Information Fusion, July 9-12 2007.

[11] Kennedy J, Eberhart R C, "Particle Swarm Optimization [A]", Proc. IEEE International Conference n Neural Networks, IV [C]. Piscataway, NJ: IEEE. Service Center, 1995. 1942-1948.

[12] Singiresu S. Rao , Engineering OptimizationTheory and Practice , Fourth EditionProc, John Wiley & Sons, Inc.,2009.

[13] E. Salim Ali and S. M. Abd-Elazim, HuiQing Cui, "Optimal PID Tuning for Load Frequency Control Using Bacteria Foraging Optimization Algorithm " , Proceedings of the 14 International Middle East Power Systems Conference (MEPCON'10), Cairo University, Egypt, December 19-21, 2010, Paper ID 191.

[14] D. H. Kim, A. Abraham, and J.H. Cho "A Hybrid Genetic Algorithm and Bacterial Foraging Approach for Global Optimization", Information Sciences, vol. 177, no. 18, September 2007, pp. 3918–3937.

[15] S. Mishra, M. Tripathy, and J.Nanda, "Multi-machine Power System Stabilizer Design by Rule Based Bacteria Foraging", Int. J. of Electric Power Systems Research vol. 77, no. 1, 2007, pp. 1595–1607.

[16] Kevin M. Passino , Biomimicry for Optimization , Control, and Automation, Berlin, Germany: Springer-Verlag.,2005.

## AUTHOR PROFILES

**Dr. Mohammed Ahmed Alhanjouri** received Bachelor of Electrical and Communications Engineering (honor) (1998), Master of Electronics Engineering (excellent) (2002) and Ph.D. in 2006. He worked as Assistant Professor, director of projects and research center, and head of computer Engineering department at Islamic University of Gaza, Palestine. Currently, he is working as Associate Professor in computer engineering dept. at IUG. His primary research interest is in the area of Artificial Intelligence. He also carries out research in many other areas such as:, Advanced digital signal processing, Pattern recognition (Image and Speech), Modern classification techniques (neural networks, Hidden Markov Models, Ant colony and Genetic Algorithm), Microcontroller applications, Cryptogaphy. Tel: 009708-280600 Ext: 2873. Email: mhanjouri@iugaza.edu.ps

**Ahmed Samy Alostaz** received bachelor of electrical engineering from islamic university of gaza , in 2008. he is postgraduate student in electrical engineering in islamic university in gaza . His fields of interest controlt are computer vision , fuzzy control and control system. Email: aostaz@gmail.com