CHAPTER 5

IMPROVED LOCATION ACCURACY USING BIO-INSPIRED OPTIMIZATION ALGORITHM

5.1 INTRODUCTION

The localization using HMM to obtain the location of the sensor nodes is discussed in the chapter 3. It is observed that the convergence of state sequence estimation helps to reduce the traffic thereby consuming less power. The limitation is that the longer the sequence better is the location accuracy. Optimizing the location accuracy is one-time process to obtain better accurate location rather than tend to converge faster.

This chapter proposes the optimization of localization strategy which uses the fitness function or the objective function obtained from HMM parameter. The existing optimizing algorithms such as PSO and BFA are vulnerable to perception of local extreme in the optimization process. In addition, PSO does not converge fast because training of HMM involves high-dimension matrices. A newer algorithm called hybrid BFA_PSO is proposed for optimizing the location of nodes using HMM parameter as fitness function. The optimized location depends on the percentage of noise that affects the distance measurement. The use of optimization techniques for locating the sensor nodes has become important in a noisy environment. The effect of movement models on hybrid BFA_PSO is analyzed and compared with the existing PSO and BFA respectively.
5.2 PROPOSED WORK

The main objective of this work is to overcome the length of the state sequence of HMM and to achieve better location accuracy by optimizing the localization using hybrid BFA_PSO. The fitness function from HMM targets to obtain the optimized location of nodes using hybrid BFA_PSO for better speed and accuracy.

5.3 MOTIVATION

Bio-inspired optimization methods are computationally efficient alternatives to analytical methods. Bio-inspired optimization algorithm is used to optimize the position accuracy of the nodes in WSN. The optimization tools such as PSO and BFA is used for image segmentation (Kulkarni & Venayagamoorthy 2010) and distributed localization has been formulated as multidimensional optimization problems. PSO-based localization is observed to be faster and BFA-based localization is more accurate. Hence to obtain the optimized location faster and accurately, the idea of PSO fused into the chemotaxis of BFA motivates to recommend hybrid BFA_PSO. The objective of the hybrid BFA_PSO is to achieve optimized location accuracy by maximizing the model likelihood probability of the HMM parameter.

5.4 SYSTEM DESIGN

The system design includes three modules namely Network model, Formulation of the fitness function from HMM and Optimized Location estimation using hybrid BFA_PSO. Each module is described in detail in the subsequent sections.
5.4.1 Network Model

The Network Model for optimized localization using Bio-inspired algorithm is the same as that referred in chapter 3, shown in Figure 3.1.

5.4.2 Formulation of Fitness Function from HMM

The main goal in HMM training from chapter 3 is to find the best $\lambda$ that maximizes $P(O/\lambda)$. The fitness function $f(\lambda)$ is obtained as:

$$f(\lambda) = \log P(O/\lambda)$$

(5.1)

$$f(\lambda) = \frac{1}{L} \sum_{l=1}^{L} \log P(O_l/\lambda)$$

(5.2)

where $O_l = [O_1, O_2, ..., O_L]$ is the $l$th observation sequence and $L$ is the number of observations. The fitness function is optimized to obtain the location accuracy in an iterative manner by using hybrid BFA_PSO and is compared with the existing PSO, BFA. To find the position accuracy, the fitness function $f(\lambda)$ is maximized and the location error is minimized.

5.4.3 Optimized Location Estimation using hybrid BFA_PSO

The objective of the hybrid BFA_PSO is to achieve optimized location accuracy by maximizing the model likelihood probability of the HMM parameter. The matrices with high dimension in the training of HMM makes PSO function slow and hence get trapped in local optima. The hybrid BFA_PSO is discussed in the following subsection.

5.4.3.1 Hybrid BFA_PSO algorithm

A new hybrid BFA_PSO algorithm is used to determine the optimized position of the randomly deployed nodes in the search space that
maximizes the fitness function $f(X) = \log P(O/\lambda)$. The fitness function is used to determine which solution is better than the others and is instrumental in determining the direction as well as magnitude of the velocity vector in each iteration.

The process for hybrid BFA_PSO is explained in Figure 5.1. The idea of PSO that has been fused into the chemotaxis of BFA is shown as bold in the algorithm. Chemotaxis is a foraging behavior that captures the process of optimization, where the non-anchor (target) nodes try to climb up to the transmission range. From its current position, target node ‘N’ will move to the position that has a minimum fitness value. The speed of the node movement is controlled by the chemotactic step size, ‘C’. The direction of movement after tumble is based on the position of every node and its velocity. At iteration ‘i’, velocity ‘$V$’ and position ‘$X$’ of each node are updated using Equations (5.3) and (5.4)

$$V_i = (V_{i-1} - 1) + c_1 * \text{rand}_1 * (pbest - X_i) + c_2 * \text{rand}_2 * (gbest - X_i) \quad (5.3)$$

$$X_i = X_{i-1} + V_i \quad (5.4)$$

Initially the values of the velocity are randomly generated within the range $[-V_m, V_m]$, where ‘$V_m$’ is the maximum value that can be assigned to any ‘$V_i$’. Thus, the movement of target node from one position to another will be the sum of current position and the step size and direction generated from PSO. By this, the nodes will move towards the global optimum position every time.
Algorithm for Hybrid BFA_PSO

1. *Initialize the Parameters* $(S, N_c, N_s, N_r, N_{ed}, P_{ed})$
2. *Set the loop indices* $K, R, J$ and $E$ to 0.
3. // *Elimination Dispersal loop:*
   4. while $E < N_{ed}$ do
   5.     $E = E + 1$
6. // *Reproduction loop:*
   7. while $R < N_r$ do
   8.     $R = R + 1$
9. // *Chemotaxis loop:*
   10. if $K < N_c$
   11.     for each node $i = 1, 2, \ldots, S$ do
   12.         // *Swim*
   13.             while $J < N_s$ do
   14.                 $J = J + 1$
   15.                 Compute $V_i = V_{i-1} + C_1 \times \text{rand}_1 \times (pbest - X_i) + C_2 \times \text{rand}_2 \times (gbest - X_i)$
   16.                 Compute $X_i = X_{i-1} + V_i$
   17.         // *Evaluate fitness function*
   18.             if $f(X_i) > f(X_{i-1})$ then
   19.                 Let $f(X_i) = f(X_{i-1})$
   20.                 Compute new node position $X_i$
   21.             else
   22.                 $J = N_s$
   23.             end if
   24.         end while
25. // *$i^{th}$ node, $K^{th}$ Chemotaxis and $R^{th}$ reproduction*

*Figure 5.1 (Continued)*
26. **Compute the health for each node i, for given R and E**
27. \[ f(X_i) = \sum_{K=1}^{NE} f(i, K, R, E) \]
28. Eliminate node having highest \( f(X_i) \) and split the other nodes in to two at the same position
29. end for
30. end if
31. end while
32. **For each node, with probability \( P_{ed} \) eliminate the node and create new node at a random position**
33. end while

**Figure 5.1 Algorithm for Hybrid BFA_PSO**

If at target node position the fitness value is lower than the previous value, the target node will move one step in the same direction with the step size and continues until a minimum fitness value is reached but only for a certain number of steps, ‘\( N_s \)’. After swims, the nodes have to tumble. Target nodes will reproduce very fast if the RSS is high and will die if less so that the population size will decrease significantly. This mechanism keeps the node’s population constant.

To model the reproduction mechanism, after ‘\( N_c \)’ chemotactic step size, the fitness values of all the target nodes are sorted in ascending order based on their accumulated cost function value. After ‘\( N_r \)’ reproduction steps, the target nodes that have probability value (between 0 and 1) lower than certain threshold value (\( P_{ed} \)) are eliminated and dispersed to another location and nodes that have probability value higher than ‘\( P_{ed} \)’ keep their current...
position. After elimination and dispersal event, node will start chemotaxis until maximum reproduction steps are achieved, followed by other elimination and dispersal events. This routine is carried out until maximum ‘$N_{ed}$’ elimination and dispersal events are achieved. The hybrid BFA_PSO is compared with existing PSO and BFA in a similar manner.

5.4.3.2 Obtaining the accuracy in the presence of noise

Kulkarni & Venayagamoorthy (2010) have estimated the node distance from a known location ‘$i$’ as

$$d_i = d_i + n_i \tag{5.5}$$

where $d_i$ is the actual distance given by

$$d_i = \sqrt{(x - x_i)^2 - (y - y_i)^2} \tag{5.6}$$

$(x, y)$ is the location of the target node and $(x_i, y_i)$ is the location of the $i^{th}$ known location in the neighbourhood of the target node. The problem of estimating a location with Gaussian additive uniform noise ‘$n_i$’ is distributed in the range $d_i \pm d_i(P_n/100)$. The result of optimized location depends on the value of percentage noise ‘$P_n$’, which affects distance measurements. The effect of varying percentage measurement noise, node variation and the iteration is analysed to obtain optimized location in a noisy environment.

5.5 SIMULATION ENVIRONMENT

The performance of the hybrid BFA_PSO, with existing PSO and BFA methods for RWM, RWP and RPGM movement models is evaluated using NS-2(2012).
Table 5.1 Simulation Parameters for hybrid BFA_PSO

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network Area</td>
<td>1000 m x 1000 m</td>
</tr>
<tr>
<td>Antenna Type</td>
<td>Omni Directional</td>
</tr>
<tr>
<td>Propagation Model</td>
<td>Two Ray Ground</td>
</tr>
<tr>
<td>Traffic Type</td>
<td>CBR</td>
</tr>
<tr>
<td>Speed</td>
<td>2 – 10 m/s</td>
</tr>
<tr>
<td>Initial Energy</td>
<td>5.1 Joules</td>
</tr>
<tr>
<td>Packet Size</td>
<td>512 bytes</td>
</tr>
<tr>
<td>Pause Time</td>
<td>5 s</td>
</tr>
<tr>
<td>Population</td>
<td>100</td>
</tr>
<tr>
<td>Percentage Noise $P_n$</td>
<td>1 -10</td>
</tr>
<tr>
<td>Acceleration constants $c_1, c_2$</td>
<td>2.0</td>
</tr>
<tr>
<td>Inertia weight ($\omega$)</td>
<td>0.5</td>
</tr>
<tr>
<td>$N_c$</td>
<td>5</td>
</tr>
<tr>
<td>$N_k$</td>
<td>20</td>
</tr>
<tr>
<td>$N_r$</td>
<td>5</td>
</tr>
<tr>
<td>$N_{ed}$</td>
<td>5</td>
</tr>
<tr>
<td>$P_{ed}$</td>
<td>0.1</td>
</tr>
<tr>
<td>Mobility Model</td>
<td>RWM, RWP, RPGM</td>
</tr>
<tr>
<td>Optimization Method</td>
<td>Hybrid BFA_PSO, PSO, BFA,</td>
</tr>
</tbody>
</table>

Table 5.1 shows the simulation parameters. Huang & Zaruba (2007a) have assumed 10% of the total nodes as anchor nodes and the network area has been deployed with 100 nodes. The simulation has been carried out for 20 runs and the average value is considered for analysis.
5.6 PERFORMANCE METRICS

The performance metrics Kulkarni & Venayagamoorthy (2010) are defined below.

- Estimation Error: It is calculated as the mean of squares of distances between actual node locations \((x, y)\) and the locations \((x_i, y_i)\), \(i = 1, 2, \ldots, N_L\) determined by optimization algorithms where \(N_L\) is the localizable nodes.

\[
Estimation\ Error = \frac{1}{N_L} \sum_{i=1}^{N_L} ((x - x_i)^2 + (y - y_i)^2) \tag{5.7}
\]

- Average Energy Dissipation: It is the average amount of energy spent by a sensor node during communication in the network.

- Number of Non localized Nodes: It is the difference of total nodes to the localizable nodes.

\[
\text{Number of Non localized nodes } N_{NL} = N - N_L \tag{5.8}
\]

5.7 SIMULATION RESULTS AND ANALYSIS

The effect of node variation, varying speeds, the iteration, percentage noise is analysed for the hybrid BFA_PSO with the existing PSO and BFA for different movement models using the simulation results.

5.7.1 Effect of varying the number of nodes

The evaluations on estimation error or localization accuracy over number of nodes for the hybrid BFA_PSO are analysed for the speed of
10 m/s. Increase in the number of nodes improves the localization accuracy for different movement models as shown in Figures 5.2, 5.3 and 5.4. As assessed, higher node density lowers the estimation error. The error estimate of hybrid BFA_PSO RWP proves to be better because each node moves near the other node with pause time at almost similar speed and direction. However, in comparison with other movement models, it has lowest relative speed since each node pauses for few seconds and nodes with RSS tend to adapt mobility and converge faster when compared with other existing work. It is seen from Figures 5.2, 5.3 that the PSO for RWM and RWP are being trapped at local minima for lesser nodes and could not reach the assigned number of nodes 20 and from Figure 5.4, for RPGM the optimization starts from 60 nodes for PSO.

![Figure 5.2 Impact of Node density on Estimation Error for BFA_PSO RWM](image)
Figure 5.3  Impact of Node density on Estimation Error for BFA_PSO RWP

Figure 5.4  Impact of Node density on Estimation Error for BFA_PSO RPGM
The evaluation on estimation error or localization accuracy over number of nodes over percentage noise $P_n$ of 0 and 5 for the hybrid BFA_PSO is analysed for the speed of 10 m/s. Increase in the number of nodes improves the localization accuracy for different movement models as shown in Figures 5.5, 5.6 and 5.7. As assessed, higher node density lowers the estimation error. The error estimate of hybrid BFA_PSO RWP proves to be better during the presence of noise. The presence of noise increases the error for all the movement models, however in comparison it has lowest relative speed because each node pauses for few seconds and nodes with RSS tend to adapt mobility and tend to converge faster when compared with other existing work.

Figure 5.5  Impact of Node density on Estimation Error on percentage noise for BFA_PSO RWM
Figure 5.6  Impact of Node density on Estimation Error on percentage noise for BFA_PSO RWP

Figure 5.7  Impact of Node density on Estimation Error on percentage noise for BFA_PSO RPGM
The effectiveness of average energy dissipated with respect to total number of nodes is shown in Figures 5.8, 5.9 and 5.10 for the speed of 10 m/s. The average energy spent when in movement is more, but actual energy spent in localization process is less. This shows that energy consumption varies due to increase in the node density. It has been observed that for different movement model, average energy dissipation gradually decreases for larger density of nodes. The existing PSO dissipates less energy for all movement models when compared with other methods. BFA has the drawback of weak ability to perceive environment and is vulnerable to perception. However, hybrid BFA_PSO RPGM consumes more power because it has to identify new node location using PSO for tumbling process when compared with other movement models.

Figure 5.8 Impact of Node density on Average Energy Dissipation for BFA_PSO RWM
Figure 5.9  Impact of Node density on Average Energy Dissipation for BFA_PSO RWP

Figure 5.10  Impact of Node density on Average Energy Dissipation for BFA_PSO RPGM
5.7.2 Effect of varying speed

The effect of varying speed over the estimation error for 100 nodes is shown in Figures 5.11, 5.12 and 5.13. As the speed increases, the localization error progressively decreases. The estimation error for RWM proves to be better for varying speeds when compared to other movement models. For increasing speed, PSO RWM behaves faster for convergence when compared with other models. However, for BFA_PSO RWM the estimation error has been improved for better searching speed to maintain the accuracy.

Figure 5.11 Impact of Speed on Estimation Error for BFA_PSO RWM
Figure 5.12 Impact of Speed on Estimation Error for BFA_PSO RWP

Figure 5.13 Impact of Speed on Estimation Error for BFA_PSO RPGM
The performance of average energy dissipation for varying speeds for 100 nodes is shown in Figures 5.14, 5.15 and 5.16. The energy has been gradually reduced due to the increase in speed for BFA_PSO RWM. In all the three movement models, the energy drops down at higher speed. For RWP and RPGM, since it pauses for a few seconds to take decision for the next movement to reach the destination, it spends more energy than RWM does. However, for RPGM movement model the energy dissipation has been more for higher speeds for 100 nodes due to the group behaviour of the nodes such as controlling the velocity of group members from that of the leader. In comparison with the methods, overall the hybrid BFA_PSO proves to be better due to behaviour of the fusion process.

![Figure 5.14 Impact of Speed on Average Energy Dissipation for BFA_PSO RWM](image)

**Figure 5.14 Impact of Speed on Average Energy Dissipation for BFA_PSO RWM**
Figure 5.15 Impact of Speed on Average Energy Dissipation for BFA_PSO RWP

Figure 5.16 Impact of Speed on Average Energy Dissipation for BFA_PSO RPGM
5.7.3 **Impact of Iterations over Nodes Localized**

The iterations over the number of nodes localized for the speed of 10 m/s are shown in Figures 5.17, 5.18 and 5.19.

![Figure 5.17 Impact of Iterations over Nodes Localized for BFA_PSO RWM](image)

**Figure 5.17 Impact of Iterations over Nodes Localized for BFA_PSO RWM**

Hybrid BFA_PSO localizes the nodes for quick iterations when compared to other methods for all movement models. The number of nodes localized increases with iterations for all the methods with varying movement model. The percentage of nodes that are localized depends on the node density and the number of anchor nodes. The hybrid BFA_PSO method localizes the node at early iterations.
Figure 5.18 Impact of Iterations over Nodes Localized for BFA_PSO RWP

Figure 5.19 Impact of Iterations over Nodes Localized for BFA_PSO RPGM
The iterations over the number of nodes localized for the speed of 10 m/s in the presence of percentage noise is shown in Figures 5.20, 5.21 and 5.22.

**Figure 5.20** Impact of Iterations over Number of Nodes Localized for Percentage Noise for BFA_PSO RWM

**Figure 5.21** Impact of Iterations over Number of Nodes Localized for Percentage Noise for BFA_PSO RWP
Hybrid BFA_PSO localizes the nodes for quick iterations when compared to other methods for all movement models. The number of nodes localized increases with iterations for all the methods with varying movement model. It is seen that for the value of $P_n = 5$, PSO RWM, RWP and the BFA RWP, RPGM takes more iterations to localize the nodes, whereas the hybrid and PSO RPGM tend to converge faster for localization. The percentage of nodes that are localized depends on the node density and the number of anchor nodes. The hybrid BFA_PSO localizes the node at early iterations.

![Figure 5.22 Impact of Iterations over Number of Nodes Localized for Percentage Noise for BFA_PSO RPGM](image)

**5.7.4 Effect of varying the percentage noise**

The evaluations on percentage noise over estimation error or localization accuracy for the hybrid BFA_PSO are analyzed with the speed of 10 m/s for 100 nodes. Increase in the percentage of noise increases the localization accuracy for different movement models as shown in Figures 5.23, 5.24 and 5.25. The error estimate of hybrid BFA_PSO RWP proves to be better because each node moves near the other node with pause.
time at almost similar speed and direction. However, in comparison with other movement models, it has lowest relative speed because nodes with RSS tend to adapt mobility and converge faster when compared with other existing work.

![Figure 5.23 Impact of Percentage Noise over Estimation Error for BFA_PSO RWM](image1)

**Figure 5.23** Impact of Percentage Noise over Estimation Error for BFA_PSO RWM

![Figure 5.24 Impact of Percentage Noise over Estimation Error for BFA_PSO RWP](image2)

**Figure 5.24** Impact of Percentage Noise over Estimation Error for BFA_PSO RWP
Figure 5.25 Impact of Percentage Noise over Estimation Error for BFA_PSO RPGM

The percentage noise over the number of non-localized nodes for the speed of 10 m/s is shown in Figures 5.26, 5.27 and 5.28.

Figure 5.26 Impact of Percentage Noise over Non Localized Nodes for BFA_PSO RWM
Figure 5.27 Impact of Percentage Noise over Non Localized Nodes for BFA_PSO RWP

Figure 5.28 Impact of Percentage Noise over Non Localized Nodes for BFA_PSO RPGM
Hybrid BFA_PSO localizes the nodes for quick iterations when compared to other methods for all movement models. The number of non-localized nodes decreases with increase in noise measurement for all the methods with varying movement model. The percentage of nodes that are non-localized depends on the accuracy and node density.

5.8 SUMMARY

The existing BFA is vulnerable to perception of local extreme in the optimization process and PSO does not converge fast because of the high-dimension matrices involved in the training of HMM. Hybrid BFA_PSO helps to obtain better-optimized location accuracy in the outdoor environment using the fitness function obtained through HMM. The approach used exploits the bio-inspired hybrid BFA_PSO to obtain the optimized location that overcomes the drawback of being trapped in local optima. The hybrid BFA_PSO RWM achieves faster localization for varying speed and achieves better-optimized location accuracy and average energy dissipation respectively than the other methods and also in noisy range environment by varying the percentage noise. The advantage of the hybrid method is it tends to converge rapidly due to fusing of PSO with the chemotaxis of BFA, which directly helps to obtain optimized location accuracy.

A new hybrid BFA_PSO algorithm is proposed for optimizing the fitness function to obtain faster and more accurate location estimation of sensor nodes. The same is discussed for the presence of noise and is analysed to obtain optimized location in a noisy environment.

The other limitation of HMM from chapter 3 is that the state duration probability has single observation and is independent of time. This drawback is overcome by proposing HSMM, which is dependent of time, obtains more accuracy than HMM is dealt in chapter 6.