CHAPTER 8
EFFICIENT GAIT RECOGNITION USING MULTI-OBJECTIVE EFFECTIVE ENHANCED ADAPTIVE FUSION TECHNIQUE BY HYBRID MPSO-BAT (EGRME^2AFHMPSOBAT) ALGORITHM

8.1. OVERVIEW
This chapter presents a detailed discussion about an efficient gait recognition based on the hybridization of multi-objective PSO and BAT algorithm. This chapter describes how the proposed gait recognition system improves the recognition accuracy and performance by using hybrid MPSO and BAT algorithm which are provided for feature fusion process.

8.2. INTRODUCTION
In the previous work, the gait recognition is achieved by using the additional gait features and is based on the multi-objective BAT algorithm. The gait velocity and depth features are measured by velocity measurement and feature vector calculation method. Thus the additional features are extracted along with the most effective, most informative less effective and shape features. The extracted features are fused together by utilizing the multi-objective BAT algorithm. The fused features are used for gait recognition process to identify the person. However, the gait recognition accuracy still requires further enhancement for recognizing an individual effectively. In addition, the multi-objective PSO algorithm has many disadvantages such as the solution is uncertain when the velocity is randomly distributed. Hence, the solution is deviated from the objective function and therefore the best solution is affected. Also, the confirmation of the new updated candidate solution is required by MPSO. To remove these drawbacks, in this research work, the hybridization of MPSO and BAT algorithm is proposed. In the proposed work, the new solution is ensured by BAT algorithm which is hybridized with the MPSO algorithm. Initially, different gait features are extracted and the extracted features are combined by utilizing the hybridization of MPSO and BAT (HMPSOBAT) algorithm (Yadav et al., 2015). Then, the fused features are classified for identifying the human gait patterns with high recognition rate. Finally, the experimental results are analysed for performance of the system.
8.3. PROPOSED GAIT RECOGNITION USING HYBRIDIZATION OF MPSO-BAT ALGORITHM

In this section, the proposed gait recognition system based on the hybrid algorithm is explained. Mainly, the proposed approach is focused on the removal of issues in multi-objective particle swarm optimization algorithm by hybridizing the BAT optimization algorithm. The issue in MPSO is that the solution is uncertain while the velocity is distributed randomly. Hence, the solution is deviated from the objective function and the best solution is affected. Therefore, the confirmation of the new updated candidate solution is needed by the MPSO. As a result, BAT optimization algorithm is hybridized with the MPSO algorithm to ensure the new solution.

Initially, the most effective and most informative less effective features with dynamic areas are extracted from the gait silhouettes by using the DFT based entropy gait representation approach. In addition, less effective features with static areas are also extracted, the shape features are extracted by using the shape descriptors. The spatio-temporal features are extracted based on the spatio-temporal interest points which are used for gender classification. Moreover, the additional gait features such as velocity moment and depth of gait are also measured and extracted. These extracted features are fused together by using the proposed algorithm which is explained below.

8.3.1. Hybrid MPSO-BAT Algorithm

In multi-objective PSO algorithm (Rini et al., 2011), the solution is uncertain while the velocity values are randomly distributed. As a result, the solution is deviated from the objective function and the best solution is also affected. Therefore, it is needed for ensuring the new updated candidate solution. This is achieved by hybridizing BAT algorithm with MPSO algorithm for selecting the new updated particle. Also, the multi-objective problem is resolved by the proposed hybrid algorithm. Initially, N number of particles is initialized. The parameters of the multi-objective function are considered as particles and each particle has its own initial velocity. In addition, the solution searching dimension is also specified. The search space for the optimized parameter \( S_i \) is denoted as \([S_i^{\text{min}}, S_i^{\text{max}}]\). The velocity of \( i^{th} \) dimension is represented as \([-v_i^{\text{max}}, v_i^{\text{max}}]\).

The objective functions are defined in terms of recognition rate, true positive, true negative, recognition time of the proposed system. The fitness function of the selected objective functions is computed including the initial position, velocity and weights.
The best particle is obtained from the initially evaluated solution. Then the obtained solution is updated by time $t$, weight $w(t)$, velocity $v_i(t)$, position $x_i(t)$, $p_{best}$ and $g_{best}$. The time $t$ is updated as $t + 1$ and the inertia weight $w(t - 1)$ is updated as $w(t)$. Moreover, the velocities of the particles are also updated by using the values of $p_{best}$ and $g_{best}$. The velocity of $n^{th}$ particle is updated in $i^{th}$ dimension and given as,

$$v_{i,n}(t) = w(t)v_{i,n}(t - 1) + c_1 \text{rand}_1(x^+_i(t - 1) - x_{i,n}(t - 1)) + c_2 \text{rand}_2(x^{**}_i(t - 1) - x_{i,n}(t - 1))$$

(8.1)

In equation (8.1), $c_1$ and $c_2$ are denoted as the positive constants and $\text{rand}_1$ and $\text{rand}_2$ are referred as the random numbers and is uniformly distributed between $(0,1)$. Also, the personal best position is denoted as $x^+_i(t - 1)$ and the global best position of $n^{th}$ dimension is referred as $x^{**}_i(t - 1)$. If the particle violates the velocity limits, then its velocity is assigned which is equivalent to the limit. The position of each particle is varied based on the updated velocities and is given as,

$$x_j(t) = x_j(t - 1) + v_j(t)$$

(8.2)

If the particle violates its position limits in any dimension, then its position is assigned at the proper limit. Therefore, each particle position is updated according to the position. If $x^+_i(t - 1)$ is best compared with $x^*_i(t)$, then the personal best position of the particle is selected as $x^+_i(t)$. Similarly, if $x^{**}_i(t - 1)$ is best compared with $x^{**}_i(t)$, then the global best position of the particle is selected as $x^{**}_i(t)$. After that, the solution is verified. If the objective functions are minimized by the solution, then the best solution is selected. Otherwise, the new best solution is generated by using the BAT algorithm. (Yang 2010).

The BAT algorithm is utilized for generating the best solution by using the non-satisfied solution of MPSO algorithm and performance of MPSO is enhanced. The Bats are flying randomly along with the velocity $v_i(t)$, position $x_i(t)$, fixed frequency $f_{min}$, wavelength $\lambda$ and loudness $A_0$. The wavelength is automatically adjusted by the emitted pulse and pulse rate changes between 0 and 1 which is depending upon the proximity effect. The loudness is varied in positive values $A_0$ to minimum constant value $A_{min}$. 

\[ \text{Equation (8.1)} \]
\[ \text{Equation (8.2)} \]
Mostly, the solution of BAT algorithm is depending on the virtual bat moment, loudness and pulse emission.

The bat population \( x_i \) is acquired from the non-satisfied solution of MPSO algorithm. Consider the searching dimension \( n \) and the fixed frequency \([f_{\text{min}}, f_{\text{max}}]\) and the wavelength \([\lambda_{\text{min}}, \lambda_{\text{max}}]\). The minimum frequency is selected as zero. The initial position of \( n^{th} \) dimension solution is selected as \( x_{i,n}(t) \). The frequency \( f_i \), velocity \( v_i(t) \) and the position \( x_i(t) \) of the new \( i^{th} \) solution is updated as follows:

\[
\begin{align*}
 f_i &= f_{\text{min}} + \text{rand}(0,1)(f_{\text{max}} - f_{\text{min}}) \\
 v_i(t) &= v_i(t-1) + f_i(x_i(t) - x(t)) \\
 x_i(t) &= x_i(t-1) + v_i(t)
\end{align*}
\]  

(8.3) \hspace{1cm} (8.4) \hspace{1cm} (8.5)

In equation (8.3), \( \text{rand}(0,1) \) is denoted as uniformly distributed random number between 0 and 1. In local search, the local solution is generated for each bat after the solution is acquired from the midst of the current best solutions and the generation of local solution is achieved by using the random walk which is given as,

\[
x_{i,\text{new},t} = x_{i,\text{old},t-1} + \text{rand}(-1,1) A_i(t)
\]

(8.6)

In equation (8.6), \( x_{i,\text{old},t-1} \) refers the old position, \( \text{rand}(-1,1) \) refers the uniformly distributed random number from -1 to 1 and \( A_i(t) \) denotes the average pulse rate of all bats at step time. In addition, pulse emission and the loudness are expressed as,

\[
A_i(t+1) = \alpha A_i(t) \\
\tau_i(t+1) = \tau_i(t)(1 - \exp(-\gamma t))
\]

(8.7) \hspace{1cm} (8.8)

In above equations, \( \alpha \) and \( \gamma \) are the constants. In order to simplify the process, the equivalent values of both \( \alpha \) and \( \gamma \) are selected. The fitness values are computed after updation is completed. If the fitness values are satisfied then the best value is selected. Otherwise iterate the solution along with the new set of non-satisfied solution of PSO algorithm.

**8.3.2. Algorithm: HMPSOBAT**

1. Initialize the N number of particle.
2. For each particle do
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3. Set initial position and velocity
4. Repeat
5. Define gait recognition accuracy as objective function (fitness value) \( f(x), x = (x_1, \ldots, x_d)^T \).
6. Determine the recognition accuracy, true positive, true negative as fitness values of each particle. The fitness is calculated by Fusion of most effective parts and shape features with adaptively selected best informative less effective part.
7. \( \text{If}(\text{fitness function} = \text{best solution}) \)
8. Update the time, inertia, weight and velocity of the particle.
9. Update the position, \( p_{best} \) and \( g_{best} \).
10. \( \text{If}(\text{Solution} = \text{best solution}) \)
11. Select the best solution
12. Else

//BAT algorithm

13. Initialize the bat population
14. Set pulse rate \( A_i(t) \) and loudness \( r_i(t) \)
15. Adjust the frequency using (8.3).
16. Update the velocity and position by using (8.4) & (8.5).
17. Generate the new solution.
18. \( \text{If}(\text{Solution} = \text{best solution}) \)
19. Select the best solution.
20. Else
21. Generate the new solution by random flying.
22. Increase the pulse rate and loudness using (8.7) & (8.8).
23. Repeat
24. Obtain the best solution
26. End if
27. End if
28. End if
29. End

Thus, the hybrid MPSO-BAT algorithm improves the recognition performance by utilizing the gait patterns effectively with less recognition time.
8.4. PERFORMANCE EVALUATION

In this section, the performance of the proposed efficient gait recognition system using hybrid MPSO-BAT algorithm is illustrated. The effectiveness of the proposed system is compared with the previous techniques in terms of precision, recall, recognition accuracy and ROC curve. According to the experimental results, the efficiency of the proposed system is demonstrated.

8.4.1. Precision

Precision is calculated based on the retrieval of information at true positive prediction and false positive. It is the fraction of fraction of recognition of parts that are similar

The comparison of precision values for proposed EGRME$^2$AFHMPSOBAT with EGRME$^2$AFBAT approach is shown in table 8.1.

<table>
<thead>
<tr>
<th>Rank</th>
<th>EGRME$^2$AFBAT</th>
<th>EGRME$^2$AFHMPSOBAT</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.77</td>
<td>0.80</td>
</tr>
<tr>
<td>4</td>
<td>0.812</td>
<td>0.848</td>
</tr>
<tr>
<td>6</td>
<td>0.86</td>
<td>0.89</td>
</tr>
<tr>
<td>8</td>
<td>0.902</td>
<td>0.927</td>
</tr>
<tr>
<td>10</td>
<td>0.946</td>
<td>0.963</td>
</tr>
</tbody>
</table>

Figure 8.1. Comparison of Precision
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Figure 8.1. shows the comparison of precision of gait recognition techniques and it is proved that the EGRME$^2$AFHMPSOBAT outperforms than existing techniques and resulted in accurate gait recognition. In the x axis, number of ranks is taken and in the y axis, precision value is taken. For example, if the rank is 10, then the precision value of EGRME$^2$AFHMPSOBAT is 0.963 which is 1.79% higher than the EGRME$^2$AFBAT. This result illustrates that the EGRME$^2$AFHMPSOBAT has high precision than all other techniques.

8.4.2. Recall

Recall is measured based on the retrieval of information at true positive prediction and false negative. The comparison of recall values for proposed EGRME$^2$AFHMPSOBAT with EGRME$^2$AFBAT approach is shown in table 8.2.

<table>
<thead>
<tr>
<th>Rank</th>
<th>EGRME$^2$AFBAT</th>
<th>EGRME$^2$AFHMPSOBAT</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.762</td>
<td>0.80</td>
</tr>
<tr>
<td>4</td>
<td>0.81</td>
<td>0.843</td>
</tr>
<tr>
<td>6</td>
<td>0.855</td>
<td>0.888</td>
</tr>
<tr>
<td>8</td>
<td>0.90</td>
<td>0.921</td>
</tr>
<tr>
<td>10</td>
<td>0.944</td>
<td>0.96</td>
</tr>
</tbody>
</table>

Figure 8.2. Comparison of Recall
Figure 8.2. shows the recall comparison of different gait recognition techniques and it is clear that the EGRME\(^2\)AFHMPSOBAT outperforms than existing techniques and resulted in accurate gait recognition with low recognition time. In the x axis, number of number of rank is taken and in the y axis, recall is taken. When the rank value is 10, the recall of EGRME\(^2\)AFHMPSOBAT is 0.96 which is 1.69% greater than the EGRME\(^2\)AFBAT. This result illustrates that the EGRME\(^2\)AFHMPSOBAT has high recall rate than all other techniques.

8.4.3. Recognition Accuracy

Accuracy means the proportion of true positives and true negatives among the total number of features examined.

The comparison of recognition accuracy values for proposed EGRME\(^2\)AFHMPSOBAT with EGRME\(^2\)AFBAT approach is shown in table 8.3.

<table>
<thead>
<tr>
<th>Rank</th>
<th>EGRME(^2)AFBAT</th>
<th>EGRME(^2)AFHMPSOBAT</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>77</td>
<td>80</td>
</tr>
<tr>
<td>4</td>
<td>81.2</td>
<td>84.8</td>
</tr>
<tr>
<td>6</td>
<td>86</td>
<td>89</td>
</tr>
<tr>
<td>8</td>
<td>90.5</td>
<td>92.7</td>
</tr>
<tr>
<td>10</td>
<td>94.6</td>
<td>97</td>
</tr>
</tbody>
</table>

Figure 8.3. Comparison of Recognition Accuracy (%)
Figure 8.3. Shows the comparison of recognition accuracy of gait recognition techniques and it is proved that the EGRME$^2$AFHMPSOBAT outperforms than existing techniques and resulted in accurate gait recognition. In the x axis, number of subjects is taken and in the y axis, recognition accuracy is taken in percentage. If the rank is 10, then the recognition accuracy value of EGRME$^2$AFHMPSOBAT is 97% which is 2.5% higher than the EGRME$^2$AFBAT. This result illustrates that the EGRME$^2$AFHMPSOBAT has high recognition accuracy than all other techniques.

8.4.4. ROC Curve

The gait recognition is evaluated by using the Receiver Operating Characteristics (ROC) curves. The ROC curve is defined as the relation between the False Rejection Ratio (FRR) and False Acceptance Ratio (FAR).

The comparison of FAR versus FRR values for proposed EGRME$^2$AFHMPSOBAT with EGRME$^2$AFBAT approach is shown in table 8.4.

Table 8.4. Comparison of FAR versus FRR

<table>
<thead>
<tr>
<th>FAR</th>
<th>EGRME$^2$AFBAT</th>
<th>EGRME$^2$AFHMPSOBAT</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.37</td>
<td>0.346</td>
</tr>
<tr>
<td>0.2</td>
<td>0.314</td>
<td>0.282</td>
</tr>
<tr>
<td>0.3</td>
<td>0.27</td>
<td>0.21</td>
</tr>
<tr>
<td>0.4</td>
<td>0.206</td>
<td>0.136</td>
</tr>
<tr>
<td>0.5</td>
<td>0.076</td>
<td>0.047</td>
</tr>
</tbody>
</table>

Figure 8.4. Comparison of ROC Curve
Figure 8.4. Shows the ROC curves comparison of different gait recognition techniques and it is clear that the EGRME\textsuperscript{2}AFHMPSOBAT outperforms than existing techniques and resulted in accurate gait recognition with low recognition time. ROC curve determination depends on the values of FAR and FRR. In the x axis, FAR is taken and in the y axis, FRR is taken. If the FAR is 0.5, then the FRR value of EGRME\textsuperscript{2}AFHMPSOBAT is 0.047 which is 38.1% lesser than the EGRME\textsuperscript{2}AFBAT. This result illustrates that the EGRME\textsuperscript{2}AFHMPSOBAT has better performance than all other techniques.

8.5. CHAPTER SUMMARY

In this chapter, the proposed work of efficient gait recognition by utilizing the hybrid MPSO-BAT algorithm is discussed. The proposed work is explored by hybridizing the MPSO and BAT algorithm in order to enhance the performance and efficiency of EGRME\textsuperscript{2}AFBAT based gait recognition. Therefore, in this work, initially, all the gait features such as most effective, more informative less effective, shape features, velocity moment and depth of the hands and legs are extracted. Then, the extracted features are selected and fused by hybrid MPSO-BAT algorithm. After that, the fused features are provided for classification in order to recognize the individual efficiently. Furthermore, the evaluation of proposed work is carried out by using CASIA B database and the performance of the proposed EGRME\textsuperscript{2}AFHMPSOBAT is compared with EGRME\textsuperscript{2}AFBAT approach. Therefore, the experimental results illustrate that the proposed EGRME\textsuperscript{2}AFHMPSOBAT method has the highest recognition accuracy than other methods.