CHAPTER 6

EFFICIENT GAIT RECOGNITION USING MULTI-OBJECTIVE ENHANCED ADAPTIVE FUSION TECHNIQUE BY BAT (EGRMEAFBAT) ALGORITHM

6.1. OVERVIEW

This chapter gives an exquisitely detailed discussion about an efficient gait recognition including gender classification using multi-objective enhanced adaptive technique based on the BAT algorithm. This chapter describes how the kernel function based Support Vector Machine (SVM) classifies the gender with an objective to reduce the gait recognition time thereby improving the performance of the system.

6.2. INTRODUCTION

Gait recognition is the most difficult process for identifying an individual effectively since it consumes more recognition time. Gait biometrics is used for identifying individuals by their walking manner. This approach is very effective since any interaction or cooperation from an individual is not required by gait recognition. Previously many techniques have been used to identify the gender of a subject using features like face, iris, fingerprints, etc. But most of these techniques require subject cooperation which is not possible for every situation. The subject cooperation was a major drawback that led many researchers to use facial images alone for gender identification. The Principal Component Analysis technique (Igual et al., 2013) is an efficient gender classification approach using facial images and gait sequence. The facial images are much easier to obtain from the still cameras or video sequences, but the quality of the facial images vary due to many reasons like distance from subject, noise, light, etc.

In the previous work discussed, the most effective gait features from dynamic body parts and most informative less effective gait features from static body parts were extracted from the human gait sequence and fused adaptively together using PSO. Though the method provided improved recognition, the exclusion of shape features reduced the performance. Hence the efficiency of gait recognition was further improved by additionally including the shape features. As the use of PSO for feature fusion is not so effective, Bat algorithm was proposed to improve the accuracy in human subject recognition.
Although the previous work provided efficient performance in terms of accurate gait recognition, the approach takes more time for matching the features of query subject to the features of each subject. As gender classification reduces the number of search subject, the time for matching can be reduced. Hence in this work, gender classification is integrated with gait recognition. Gender classification is performed by including the Sparse spatio-temporal features to classify the gender of the subject. The structural differences between male and female walkers, such as the shoulder-hip ratio, center-of-moment features of the torso, and the temporal dynamic factors such as arm swing and shoulder sway are analyzed. For extracting the Sparse spatio-temporal features, the interest points are detected using Harris corner detector with simulated annealing approach. The most effective features, more informative less effective features and shape features are extracted as illustrated in the previous chapters and fused together using BAT while efficient classifiers are used to classify the subject based on their gender. In this work Sparse Multi-kernel Support Vector Machine (SM-SVM) is used to provide efficient gender classification. Thus the gender of the subject can be identified effectively and can be utilized to improve the gait recognition.

At last, the classification and recognition performance is analyzed through the experimental results.

6.3. OVERVIEW OF PROPOSED SYSTEM

The proposed gait-based gender classification is achieved by using the different features such as most effective features, most informative less effective features and shape feature. These features are extracted from the silhouettes and shape descriptors. The required features are selected by using the adaptive technique which utilizes the threshold value along with the best fitness value. Then the selected features are fused together based on the BAT algorithm for improving the efficiency of the gait recognition. The algorithm of GRMEAFBAT is briefly explained in Chapter 5. However, the recognition time is high in GRMEAFBAT due to the matching the features in recognition process. Therefore, the recognition time is reduced by the proposed gait-based gender classification where the classification of gender is included with the gait recognition for identifying the individuals.

6.4. PROPOSED EGRMEAFBAT ALGORITHM

The proposed gait-based gender classification system utilizes the additional features such as sparse spatio-temporal features along with the most effective, most
informative less effective and shape features for recognizing the gender of the subject. The spatio-temporal features can be extracted by detecting the interest points. The interest points are detected within the video silhouettes and are treated as the central points. A cuboid of pixel values are extracted around these central points and processed to form the spatiotemporal descriptor. At every point, response function is computed for which the interest points acts as local maxima.

The spatio-temporal scale space is represented by convolving of the silhouette image with a Gaussian smoothing kernel applied to the spatial domain. Let the silhouette image be $I(x, y)$. The corresponding Gaussian smoothing kernel is $G(x, y, \sigma)$ where the parameter $\sigma$ is the spatial scale. The presence of spatial scale $\sigma$ and temporal scale $\tau$ determines that the image has interest points such as corners and edges. Hence the image from the silhouette can be represented in the form of a cube $I(x, y, t)$ containing stack of images. The response function $R$ can be given by

$$R = (I * g * h_{ev})^2 + (I * g * h_{od})^2$$ (6.1)

In equation (6.1), $I$ refers the image cube, $g$ refers the Gaussian smoothing kernel, $h_{ev}$ and $h_{od}$ are the quadrative pair of 1D Gabor filters which are applied along the temporal plane after the occurrence of initial spatial smoothing which are defined as follows in equation (6.2) and (6.3)

$$h_{ev}(t, \tau, \omega) = -\cos (2\pi t \omega) e^{-t^2 / \tau^2}$$ (6.2)

$$h_{od}(t, \tau, \omega) = -\sin (2\pi t \omega) e^{-t^2 / \tau^2}$$ (6.3)

Where $\omega = 4 / \tau s$

Thus, the image pre-processing is performed and then the spatio- temporal corners are identified by computing the interest points by using the improved Harris detector which is enhanced based on the simulated annealing.

6.4.1 Improved Harris Detector using Simulated Annealing

In Harris corner detector (Harris and Stephens 1988), the gradients of the image are identified along $x$, $y$ and $t$ dimensions. The spatiotemporal corners are referred as the regions in which the gradient directions are orthogonal over the three dimensions. Therefore, the detection of the spatio-temporal interest points is very effective. In the proposed approach, the detection is further improved by introducing the simulated
annealing in the Harris detector. The corner interest points in the spatial domain are extracted by Harris detector when the local image around the selected corner interest point is enhanced by simulated annealing. The first order approximation of patch shifts are utilized by the Harris corner detector for determining the sum of squared differences as the bilinear function of the shift. The interest points are identified by utilizing the shift and given as,

\[ E(u, v) = \sum_{x,y} w(x, y) [I(x + u, y + v) - I(x, y)]^2 \]  

(6.4)

In equation (6.4), \( w(x, y) \) refers the window weighting function, \( I(x + u, y + v) \) refers the shifted intensity and \( I(x, y) \) is the original intensity for the interest points. The intensity of the corner and edge points is given by the Harris corner detection. The major objective of the Harris detector is detecting the value of edges and corner. It is required for detecting the variations of the corner patch in the all directions and is given by equation (6.5)

\[ E_{u,v}(x, y) = [uv] M \begin{bmatrix} u \\ v \end{bmatrix} \]  

(6.5)

In equation (6.5), \( M \) is the \( 2 \times 2 \) matrix which is computed from the image derivatives and given as,

\[ M = \sum_{x,y} w(x, y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \]  

(6.6)

In equation (6.6), \( I_x, I_y \) denotes the components of the image gradients. The Eigen values of \( M \) are estimated for determining the change in direction. The computation of Eigen values is given as in equation (6.7),

\[ C(M) = \det(M) + k \times tr^2(M) \]  

(6.7)

The corner points are detected by the Harris detector by using the change in direction and the image locally around these corner points are enhanced by simulated annealing. The simulated annealing performs with the limited speed for discovering the all corners and edge locations. Therefore, the better solution of image enhancement around the corner interest points is obtained. The detected temporal points are required for extracting the spatio-temporal features. The features are fused together by using the BAT algorithm and then the fused features are classified for determining the gender according to the features.
Figure 6.1. Detection of Interest Points using Harris Corner Detection
Figure 6.2. Detection of Interest Points using Improved Harris Corner Detection

Figure 6.1. and Figure 6.2. shows the detection of interest points using Harris corner detection method and improved Harris corner detection method. Here, x-axis and y-axis are denoted as rotated angle in degrees. Figure 6.2 shows the detection of interest points effectively by using Improved Harris Corner detection whereas the efficiency of detection of interest points using Harris Corner detection algorithm is less.
6.4.2. Sparse Multi-kernel Support Vector Machine

After, the detection of sparse spatio-temporal interest points like edge and corner points, the extraction and fusion of the features are obtained and the classification of features into the gender classes is also performed. The Sparse Multi-kernel Support Vector Machine (SM-SVM) (Hu et al., 2009) is utilized for the gender classification which is a linear combination of kernel approach. The SM-SVM method is achieved by integrating the multiple equivalent kernels with the SVM classifier.

Let N base kernels be $K_1, K_2, ..., K_N$ which has corresponding equivalent kernels, $K_1^z, K_2^z, ..., K_N^z$. New kernels can be generated for SVM approach using the feature locations. The multiple kernels are presented with multiple objectives. The SM-SVM classifier trains the image fused features with optimized objective functions. The testing of the features is based on the kernel decision functions. The multiple kernel function is given as,

$$K^z(x_i, x_j) = \sum_{k=1}^{N} \mu_k K^z_k(x_i, x_j); k = 1 \text{ to } N$$  (6.8)

In equation (6.8), $K^z_k(x_i, x_j)$ refers to the kernel generated according to the corners and $\mu$ refers the sparse solution. By using the equation (6.8), the SVM decision function is given as follows,

$$g(x) = \sum_{i} a_i y_i K^z(x_i, x_j) - b$$  (6.9)

In equation (6.9), $b$ denotes the hyperplane of vector, $a_i$ represents the fused feature, and $y_i$ refers the class to which the feature $a_i$ belongs like male or female. The single kernel SVM may be slower at some points which can be overcome by SM-SVM classifier. The SM-SVM provides efficient gender classification with better accuracy. Then the gender classification can be used to reduce the search space in gait recognition. Then the features are used in recognition of human gait by determining the Euclidean distance. The use of gender in gait recognition reduces the number of search objects and also improves the accuracy of recognition.

6.4.3. Algorithm: Gender Classification

1. Begin
2. Class 1 = Male; Class 2 = Female;
3. Consider $\{x_1, x_2, ..., x_n\}$ as training set with $n$ video clips.
4. Extract silhouettes S with P frames.

5. Totalframes = \sum_i P_i frames

//Pre-processing

6. Extract the most effective, more informative less effective and shape features.

7. Detect the corner points by using the improved Harris detector.

8. Compute x and y derivatives of the image.

\[ I_x = G_x * I; \quad I_y = G_y * I \]  \hspace{1cm} (6.10)

9. Compute the products of derivatives at each pixel.

\[ I_x^2 = I_x I_x; \quad I_y^2 = I_y I_y; \quad I_{xy} = I_x I_y \] \hspace{1cm} (6.11)

10. Compute the sum of product of derivatives at every pixel.

\[ S_x = G_{at} * I_x^2; \quad S_y = G_{at} * I_y^2; \quad S_{xy} = G_{at} * I_{xy} \] \hspace{1cm} (6.12)

11. Define the matrix at every pixel \((x, y)\).

\[ H(x, y) = \begin{bmatrix} S_x(x, y) & S_{xy}(x, y) \\ S_{xy}(x, y) & S_y(x, y) \end{bmatrix} \] \hspace{1cm} (6.13)

12. Determine the response of the detector at every pixel.

\[ R = \text{Det}(H) - k(\text{Trace}(H))^2 \] \hspace{1cm} (6.14)

13. Compute the interest points by utilizing the equation (6.4).

14. Compute the Eigen value of each point by using the equation (6.7).

15. Keep the threshold value T based on the R.

16. Consider corner \(H = H_0\).

17. For \(k = 0\) to \(k_{\text{max}}\)

18. Select the random neighbor corner as \(H_{\text{new}}\).

19. Check threshold value T for image quality.

20. \(If(Q(H_{\text{new}}) > Q(H)) \hspace{1cm} //Q-Image quality\)

21. \(H = H_{\text{new}}\)

22. End if

//Extraction of spatio-temporal features

23. Fusion of features.

24. End for

25. Apply SM-SVM.
26. For each feature \( a_i \) satisfies \( g(x) = 0 \).

27. Compute \( g(x) \) by using the equation (6.9).

28. If \( g(x) \geq 1 \) then

29. \( a_i = \text{Class 1} \)

30. If \( g(x) \leq -1 \) then

31. \( a_i = \text{Class 2} \)

32. End if

33. End for

Thus the gender recognition is utilized for gait recognition to reduce the recognition time and search space of the gait recognition system.

### 6.5. PERFORMANCE EVALUATION

In this section, the performance of the proposed gender-based gait recognition system using 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.

#### 6.5.1. 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 EGRMEAFBAT with GRMEAFPSO, GRMEAFBAT approach is shown in table 6.1.

<table>
<thead>
<tr>
<th>Rank</th>
<th>GRMEAFPSO</th>
<th>GRMEAFBAT</th>
<th>EGRMEAFBAT</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.69</td>
<td>0.72</td>
<td>0.752</td>
</tr>
<tr>
<td>4</td>
<td>0.731</td>
<td>0.76</td>
<td>0.791</td>
</tr>
<tr>
<td>6</td>
<td>0.795</td>
<td>0.80</td>
<td>0.84</td>
</tr>
<tr>
<td>8</td>
<td>0.86</td>
<td>0.871</td>
<td>0.893</td>
</tr>
<tr>
<td>10</td>
<td>0.881</td>
<td>0.918</td>
<td>0.93</td>
</tr>
</tbody>
</table>
Figure 6.3. Comparison of Precision

Figure 6.3. shows the comparison of precision of gait recognition techniques and it is proved that the EGRMEEAFBAT 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 EGRMEEAFBAT is 0.93 which is 5.5% higher than the GRMEEAFPSO and 1.3% more than GRMEEAFBAT. This result illustrates that the EGRMEEAFBAT has high precision than all other techniques.

6.5.2. Recall

Recall is measured based on the retrieval of information at true positive prediction and false negative.

The comparison of recall values for proposed EGRMEEAFBAT with GRMEEAFPSO, GRMEEAFBAT approach is shown in table 6.2.
Table 6.2. Comparison of Recall

<table>
<thead>
<tr>
<th>Rank</th>
<th>GRMEAFPSO</th>
<th>GRMEAFBAT</th>
<th>EGRMEAFBAT</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.683</td>
<td>0.717</td>
<td>0.75</td>
</tr>
<tr>
<td>4</td>
<td>0.73</td>
<td>0.75</td>
<td>0.789</td>
</tr>
<tr>
<td>6</td>
<td>0.792</td>
<td>0.798</td>
<td>0.836</td>
</tr>
<tr>
<td>8</td>
<td>0.859</td>
<td>0.87</td>
<td>0.889</td>
</tr>
<tr>
<td>10</td>
<td>0.88</td>
<td>0.915</td>
<td>0.923</td>
</tr>
</tbody>
</table>

Figure 6.4. Comparison of Recall

Figure 6.4. shows the recall comparison of different gait recognition techniques and it is clear that the EGRMEAFBAT outperforms than other 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 EGRMEAFBAT is 0.923 which is 4.8% higher than GRMEAFPSO and also 0.8% more than GRMEAFBAT. This result illustrates that the EGRMEAFBAT has high recall rate than all other techniques.
6.5.3. 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 EGRMEAFBAT with GRMEAFPSO, GRMEAFBAT approach is shown in table 6.3.

<table>
<thead>
<tr>
<th>Rank</th>
<th>GRMEAFPSO</th>
<th>GRMEAFBAT</th>
<th>EGRMEAFBAT</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>69</td>
<td>72</td>
<td>75.2</td>
</tr>
<tr>
<td>4</td>
<td>73.1</td>
<td>76</td>
<td>79.1</td>
</tr>
<tr>
<td>6</td>
<td>79.5</td>
<td>82</td>
<td>84</td>
</tr>
<tr>
<td>8</td>
<td>85</td>
<td>86.5</td>
<td>88.3</td>
</tr>
<tr>
<td>10</td>
<td>88.1</td>
<td>91.8</td>
<td>93</td>
</tr>
</tbody>
</table>

Figure 6.5. Comparison of Recognition Accuracy (%)

Figure 6.5. shows the comparison of recognition accuracy of gait recognition techniques and it is proved that the EGRMEAFBAT outperforms other 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 EGRMEAFBAT is 93% which is 5.5% higher than GRMEAFPSO and 1.3% higher than GRMEAFBAT. This result illustrates that the EGRMEAFBAT has high recognition accuracy than all other techniques.

6.5.4. 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 EGRMEAFBAT with GRMEAFPSO, GRMEAFBAT approach is shown in table 6.4.

<table>
<thead>
<tr>
<th>FAR</th>
<th>GRMEAFPSO</th>
<th>GRMEAFBAT</th>
<th>EGRMEAFBAT</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.48</td>
<td>0.451</td>
<td>0.427</td>
</tr>
<tr>
<td>0.2</td>
<td>0.41</td>
<td>0.398</td>
<td>0.37</td>
</tr>
<tr>
<td>0.3</td>
<td>0.35</td>
<td>0.341</td>
<td>0.316</td>
</tr>
<tr>
<td>0.4</td>
<td>0.29</td>
<td>0.27</td>
<td>0.25</td>
</tr>
<tr>
<td>0.5</td>
<td>0.24</td>
<td>0.218</td>
<td>0.19</td>
</tr>
</tbody>
</table>

Figure 6.6. Comparison of ROC Curve
Figure 6.6. shows the ROC curves comparison of different gait recognition techniques and it is clear that the EGRMEAFBAT outperforms other 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 EGRMEAFBAT is 0.19 which is 20.8% lesser than the GRMEAFPSO and 12.8% lower than the GRMEAFBAT. This result illustrates that the EGRMEAFBAT has better performance than all other techniques.

6.6. CHAPTER SUMMARY

In this chapter, the proposed work of gait recognition by utilizing the gender classification is discussed. In this work, initially, the gender classification is performed for identifying the gender by using the improved Harris corner detector and SM-SVM classification techniques. Once, the gender is identified then the gait recognition is performed thereby reducing the search space of the recognition system. Moreover, the most effective, more informative less effective and shape features are also extracted and utilized for gait recognition process by using the BAT algorithm. The evaluation of proposed work is carried out by using CASIA B database and the performance of the proposed EGRMEAFBAT is compared with GRMEAFPSO and GRMEAFBAT approach. The experimental results illustrate that the proposed EGRMEAFBAT method has better accuracy than other methods.