SYMBOLIC REPRESENTATION AND RECOGNITION OF GAIT : AN APPROACH BASED ON LBP OF SPLIT GAIT ENERGY IMAGES

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ABSTRACT

Gait is one of the biometric techniques used to identify an individual from a distance by his/her walking style. Gait can be recognized by studying the static and dynamic part variations of individual body contour during walk. In this paper, an interval value based representation and recognition of gait using local binary pattern (LBP) of split gait energy images is proposed. The gait energy image (GEI) of a subject is split into four equal regions. LBP technique is applied to each region to extract features and the extracted features are well organized. The proposed representation technique is capable of capturing variations in gait due to change in cloth, carrying a bag and different instances of normal walking conditions more effectively. Experiments are conducted on the standard and considerably large database (CASIA database B) and newly created University of Mysore (UOM) gait dataset to study the efficacy of the proposed gait recognition system. The proposed system being robust to handle variations has shown significant improvement in recognition rate.

KEYWORDS

Gait Recognition, Gait energy image, Interval-valued features, Local binary pattern, Representation, Symbolic data, Similarity measure

1. INTRODUCTION

Gait is a manner of walking of an individual. Gait recognition is a method of identifying or verifying an individual based on his/her walking style. Gait recognition has gained much attention in recent years in the field of computer vision because of its ability to deal with low resolution images captured at a considerable distance away from the camera without the individual's cooperation. Gait can be used in situations when other biometric traits such as face, iris and fingerprint information do not have sufficient resolution for recognition. Gait as a biometric source can be used in some monitoring applications for early warnings if any, suspicious threats are found. Though several techniques have been proposed for efficient gait recognition, the methods have some limitations in terms of time complexity, storage requirements, recognition rate and works under some constraints. So there is a scope for exploring further the robust techniques for gait recognition.

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2. RELATED WORK

Several attempts have been made by many researchers to provide an efficient and effective gait recognition system. Following are the few interesting works found in the literature in this direction.

Han et al. [1] introduced Gait energy image, which consist of spatio-temporal information. Recognition is achieved by combining real and synthetic templates (poses). USF Gait database is used for experimentation and the study shows satisfactory results. Pratik chattopadhyay et al. [2] proposed pose depth volume (PDV) gait feature for frontal view gait recognition. The method combines both colour and depth information in the extracted feature. A PDV is constructed by averaging voxel volumes of depth key pose frames. It consists of both shape and depth variations over each depth key pose in a gait cycle of individual walking sequence. Dataset used is captured in an indoor environment using Microsoft kinect. Experiment is conducted on 30 subjects and author claimed acceptable results. Jeevan et al. [3] proposed gait recognition using Pal and Pal Entropy. PCA is applied on the feature matrix and Support Vector Machine is used for classification. The author compares the result with Shannon Entropy and achieved reasonable result. Sudeep Sarkar et al. [4] proposed a baseline algorithm which consists of 12 experiments. Recognition is achieved through frame correlations between successive frames using Tanimoto similarity measure. Recognition rate for 12 experiments varies from 78% on the easiest to 3% on the hardest experiment. AmitKale et al. [5] proposed a method for gait recognition, which uses the binary silhouette width as features. The feature incorporates both structural and dynamic information of an individual. Experimental results have shown that the method has better recognition rate for side view compared to frontal view. Dupuis et al. [6] proposed the Random Forest (RF) algorithm which is based on the bootstrap-aggregating concept to rank features importance to address the problem of high dimensional feature space in model-free approach. In order to efficiently search throughout subspaces, they have applied a backward feature elimination search strategy. Authors have claimed that their approach can greatly reduce the complexity of the classification problem while achieving fair correct classification rates when gait is captured with unknown conditions.

Most of the techniques proposed in the literature for gait recognition incorporate the features extracted from each silhouette of a gait sequence. Since each gait sequence has considerably more number of silhouettes, the process of feature extraction, representation and matching for gait recognition becomes complex and time consuming for real time applications. In order to overcome this limitation, in this work, the idea of GEI has been explored and the suitability of texture feature extraction technique such as LBP is studied. GEI image is divided into four equal parts to localize the variations in each part and LBP features are extracted from each part. The extracted features are organized in a clock wise direction to preserve the sequence. Sequence preservation is very much essential for matching and recognition.

The gait of an individual person may vary due to change in cloth, change in shoe, change in surface, carrying a bag etc. Also it has been observed that there will be some variations even in normal walking condition at different point of time. The conventional data analysis techniques may fail to capture such variations effectively. From the literature survey, we understand that the concept of symbolic data analysis has been well studied in the field of cluster analysis [7, 8, 9, 10, 11, 12], shape analysis [13] and signature biometric applications [14]. Also suitability of symbolic data analysis approach for gait recognition is attempted recently in [15, 16, 17, 18]. These unconventional techniques have proved that they outperform the conventional techniques in terms of performance and uncertainty. Thus, we propose to incorporate the concept of symbolic data analysis particularly the interval type data to capture the variations and to effectively represent the gait information in the knowledge base used for the purpose of recognition. Performance of the proposed gait recognition system is studied by conducting experiments on the CASIA B and UOM gait databases. Rest of the paper is organized as follows. Section 3 presents proposed methodology for gait recognition. Experimental results are presented in section 4, followed by discussion and conclusion in section 5.

3. PROPOSED METHODOLOGY

The proposed method of gait recognition system uses GEI and LBP technique to extract features for gait representation. The method involves the following steps: In the first step, Gait Energy Image (GEI) is generated using sequence of silhouettes of a gait cycle. In the second step, GEI is divided into four equal parts. In the third step, LBP operator is applied to extract features from each part of GEI separately and then concatenated for representation. The feature extraction process is applied to all instances (different covariates such as wearing coat, carrying a bag and different normal conditions) of a subject and the corresponding features are consolidated to form an interval-valued feature vector representing a subject in the gait knowledgebase. In the fourth step, a suitable similarity measure is used to match probe gait with reference gait and a matching score is computed for recognition. The following subsections describe these steps in detail.

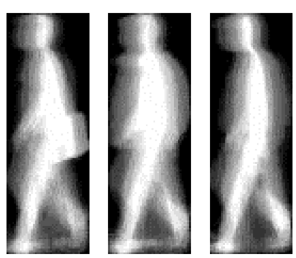
3.1. Gait energy image

In order to reduce the complexity in characterizing a gait, the silhouettes of a gait cycle are aggregated using the idea proposed by [1] to produce a single image called Gait Energy Image (GEI). GEI for a gait cycle is computed by taking the average of all silhouettes over a gait cycle and is defined by

$$GEI = G(x, y) = \frac{1}{T}\sum_{t=1}^{T} I(x, y, t) \tag{1}$$

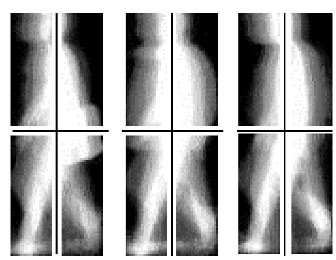
Where T is the number of frames in a gait cycle, I is a gait silhouette image, x and y are pixel coordinates and t is the frame number in a sequence of silhouettes of a gait cycle.

Fig. 1 shows the examples of GEIs computed for same subject in three different instances (a) carrying a bag (b) with coat and (c) normal and Fig. 2 shows the same GEIs divided into four equal parts.



(a) (b) (c)

Figure 1



(a) (b) (c)

Figure 2

3.2. Feature extraction

Features are extracted from GEI to characterize the gait. The idea of LBP proposed in [19] is used to extract the features. LBP is a gray scale texture operator which describes local texture pattern with a binary code. A binary pattern number for a central pixel is obtained by comparing the gray value of central pixel with gray values of its neighbourhood pixels as shown below.

$$LBP_{P,R}(x_c, y_c) = \sum_{P=0}^{P-1} s(g_p - g_c) 2^p \quad (2)$$

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (3)$$

Where g_c is the gray value of the center pixel (x_c, y_c) and g_p is the gray value of its neighbours in the *P* sampling points plane. *P* is the number of neighbours and *R* is the radius of the neighbourhood.

In this work, we used uniform LBP pattern with *P* = 8 and *R* = 1, to extract 59 bin values as features. From each part of GEI, 59 feature values are extracted. Since, the feature values are extracted from four different parts of GEI, totally 236 feature values are used to represent each gait of a subject. The more theoretical description about uniform LBP pattern is found in [20].

3.3. Representation

Since the gait of a person varies slightly due to change in carrying conditions, change in clothes and different normal conditions, the LBP features obtained for these instances (covariates) also contain variations. These variations are handled by consolidating the features in the form of an interval type data as explained below.

$$\text{Let } S = [S_1, S_2, K\ S_I, K\ K\ S_N] \quad (4)$$

be the *N* number of subjects.

$$\text{Let } S_I = \{s_I^1, s_I^2, \Lambda, s_I^j, \Lambda, s_I^n\} \quad (5)$$

be the *n* instances of the subject S_I.

LBP features extracted separately from four different parts of GEI (Fig. 2) in a clockwise direction, numbered as 1,2,3 and 4 for an instance s_I^j of subject S_I is given as

$$s_I^j = [\{F1\}, \{F2\}, \{F3\}, \{F4\}] \quad (6)$$

Where

$$F1 = \{f1_{I1}^j, f1_{I2}^j, \Lambda, f1_{Ik}^j, \Lambda, \Lambda, f1_{\mathrm{Im}}^j\} \quad (7)$$

$$F2 = \{f2_{I1}^j, f2_{I2}^j, \Lambda, f2_{Ik}^j, \Lambda, \Lambda, f2_{\mathrm{Im}}^j\} \quad (8)$$

$$F3 = \{f3_{I1}^j, f3_{I2}^j, \Lambda, f3_{Ik}^j, \Lambda, \Lambda, f3_{\mathrm{Im}}^j\} \quad (9)$$

$$F4 = \{f4_{I1}^j, f4_{I2}^j, \Lambda, f4_{Ik}^j, \Lambda, \Lambda, f4_{\mathrm{Im}}^j\} \quad (10)$$

and *m* is the number of LBP features.

The mean and standard deviation of k^{th} feature of first part *F*1 of all the instances of S_I is given by

$$\mu1_{Ik} = mean\left(f1_{Ik}^1, f1_{Ik}^2, \Lambda, f1_{Ik}^j, \Lambda\ f1_{Ik}^n\right) \quad (11)$$

$$\sigma1_{Ik} = std\left(f1_{Ik}^1, f1_{Ik}^2, \Lambda, f1_{Ik}^j, \Lambda\ f1_{Ik}^n\right) \quad (12)$$

Similarly the mean and standard deviation of k^{th} feature of second (*F*2), third (*F*3) and fourth (*F*4) part of all the instances of S_I is computed as follows:

$$\mu 2_{Ik} = mean\left(f2^{1}_{Ik}, f2^{2}_{Ik}, \Lambda, f2^{j}_{Ik}, \Lambda\ f2^{n}_{Ik}\right) \tag{13}$$
$$\sigma 2_{Ik} = std\left(f2^{1}_{Ik}, f2^{2}_{Ik}, \Lambda, f2^{j}_{Ik}, \Lambda\ f2^{n}_{Ik}\right) \tag{14}$$
$$\mu 3_{Ik} = mean\left(f3^{1}_{Ik}, f3^{2}_{Ik}, \Lambda, f3^{j}_{Ik}, \Lambda\ f3^{n}_{Ik}\right) \tag{15}$$
$$\sigma 3_{Ik} = std\left(f3^{1}_{Ik}, f3^{2}_{Ik}, \Lambda, f3^{j}_{Ik}, \Lambda\ f3^{n}_{Ik}\right) \tag{16}$$
$$\mu 4_{Ik} = mean\left(f4^{1}_{Ik}, f4^{2}_{Ik}, \Lambda, f4^{j}_{Ik}, \Lambda\ f4^{n}_{Ik}\right) \tag{17}$$
$$\sigma 4_{Ik} = std\left(f4^{1}_{Ik}, f4^{2}_{Ik}, \Lambda, f4^{j}_{Ik}, \Lambda\ f4^{n}_{Ik}\right) \tag{18}$$

The minimum and maximum value of the k^{th} feature of first part $F1$ of all the instances of S_I is given by

$$f1^{-}_{Ik} = \mu 1_{Ik} - \sigma 1_{Ik} \tag{19}$$
$$f1^{+}_{Ik} = \mu 1_{Ik} + \sigma 1_{Ik} \tag{20}$$

Similarly the minimum and maximum value of k^{th} feature of second ($F2$), third ($F3$) and fourth ($F4$) part of all the instances of S_I is given by

$$f2^{-}_{Ik} = \mu 2_{Ik} - \sigma 2_{Ik} \tag{21}$$
$$f2^{+}_{Ik} = \mu 2_{Ik} + \sigma 2_{Ik} \tag{22}$$
$$f3^{-}_{Ik} = \mu 3_{Ik} - \sigma 3_{Ik} \tag{23}$$
$$f3^{+}_{Ik} = \mu 3_{Ik} + \sigma 3_{Ik} \tag{24}$$
$$f4^{-}_{Ik} = \mu 4_{Ik} - \sigma 4_{Ik} \tag{25}$$
$$f4^{+}_{Ik} = \mu 4_{Ik} + \sigma 4_{Ik} \tag{26}$$

Thus, the reference gait of a subject S_I (I = 1,2,..,N) in the knowledge base is represented in the form of interval-valued type symbolic feature vector as follows:

$$S_I = \left[\{RF1_I\}, \{RF2_I\}, \{RF3_I\}, \{RF4_I\}\right] \tag{27}$$

Where

$$RF1_I = \left\{rf1_{I1}, rf1_{I2}, \Lambda, rf1_{Ik}, \Lambda, rf1_{\mathrm{Im}}\right\} \tag{28}$$
$$RF2_I = \left\{rf2_{I1}, rf2_{I2}, \Lambda, rf2_{Ik}, \Lambda, rf2_{\mathrm{Im}}\right\} \tag{29}$$
$$RF3_I = \left\{rf3_{I1}, rf3_{I2}, \Lambda, rf3_{Ik}, \Lambda, rf3_{\mathrm{Im}}\right\} \tag{30}$$
$$RF4_I = \left\{rf4_{I1}, rf4_{I2}, \Lambda, rf4_{Ik}, \Lambda, rf4_{\mathrm{Im}}\right\} \tag{31}$$

and

$$rf1_{Ik} = \left\{f1^{-}_{Ik}, f1^{+}_{Ik}\right\} \tag{32}$$
$$rf2_{Ik} = \left\{f2^{-}_{Ik}, f2^{+}_{Ik}\right\} \tag{33}$$
$$rf3_{Ik} = \left\{f3^{-}_{Ik}, f3^{+}_{Ik}\right\} \tag{34}$$
$$rf4_{Ik} = \left\{f4^{-}_{Ik}, f4^{+}_{Ik}\right\} \tag{35}$$

The probe gait of a subject S_I is also characterized with LBP features as described earlier but with only one instance (covariate). Thus the feature vector representing probe gait is a crisp vector as follows:

$$s_P = \left[\{PF1\}, \{PF2\}, \{PF3\}, \{PF4\}\right] \tag{36}$$

Where

$$PF1 = \{f1_1, f1_2, \Lambda, f1_k, \Lambda, f1_m\} \quad (37)$$

$$PF2 = \{f2_1, f2_2, \Lambda, f2_k, \Lambda, f2_m\} \quad (38)$$

$$PF3 = \{f3_1, f3_2, \Lambda, f3_k, \Lambda, f3_m\} \quad (39)$$

$$PF4 = \{f4_1, f4_2, \Lambda, f4_k, \Lambda, f4_m\} \quad (40)$$

Table 1 shows only the 1^{st}, 2^{nd} and 59^{th} feature values extracted from part-1, part-2, part-3 and part-4 of GEI of different instances (covariates) of a subject S_I as an example. Table 2 shows the interval-valued representation of the 1^{st}, 2^{nd} and 59^{th} feature values of all the four parts of GEI for a subject S_I.

Table 1. Crisp feature values extracted from first, second, third and fourth GEI part of different instances (covariates) of a subject.

	GEI Part 1				**GEI Part 2**			
Feature No	**1**	**2**	**…**	**59**	**1**	**2**	**..**	**59**
Bag1	24	36	…	161	24	48	..	129
Cloth1	19	34	…	159	28	52	..	130
Normal1	11	30	…	152	21	41	..	119
Normal2	13	29	…	157	17	39	..	123
Normal3	10	26	…	140	19	44	..	120
	GEI Part 3				**GEI Part 4**			
Feature No	**1**	**2**	**…**	**59**	**1**	**2**	**..**	**59**
Bag1	18	57	…	209	27	92	..	112
Cloth1	18	63	…	196	29	86	..	116
Normal1	13	52	…	189	20	77	..	108
Normal2	11	49	…	200	26	83	..	103
Normal3	16	54	…	192	24	84	..	99

Table 2. Interval valued features representing a subject.

GEI Part 1		**GEI Part 2**	
Feature No	**Interval**	**Feature No**	**Interval**
1	[9.45 , 21.34]	1	[17.47, 26.12]
2	[27.00, 35.00]	2	[39.53, 50.06]
…	…	…	…
59	[145.39, 162.20]	59	[119.13, 129.26]
GEI Part 3		**GEI Part 4**	
Feature No	**Interval**	**Feature No**	**Interval**
1	[12.08, 18.31]	1	[21.77, 28.62]
2	[49.66, 60.33]	2	[78.98, 89.81]
…	…	…	…
59	[189.40, 204.99]	59	[100.79, 114.40]

3.4. Similarity computation

In order to recognize a probe gait S_P, features are extracted from the probe gait as discussed in sub section 3.2 of section 3 and represented as shown in Equation 36. As an example, only a few feature values of type crisp of a probe gait S_P is shown in Table 3. The obtained crisp feature vector of a probe gait is compared with the symbolic feature vectors of reference gaits Equation 27 in the gait knowledge-base and a matching score is computed for recognition.

Table 3. Few crisp feature values representing probe gait.

Feature No	GEI Part 1	GEI Part 2	GEI Part 3	GEI Part 4
1	20	29	14	29
2	37	43	59	77
…	…	…	…	…
59	157	116	201	110

The Similarity measure suggested in [21] is found to be suitable and hence used for computing similarity between reference gaits and probe gait as described below.

$$TotalSimilarity\left(S_p, S_I\right) = \sum_{x=1}^{4} \sum_{k=1}^{m} sim\left(f\,x_k, \left[f\,x_{Ik}^{-}, f\,x_{Ik}^{+}\right]\right) \qquad (41)$$

$$for\ I = 1\ to\ N$$

Where

$$sim\left(f\,x_k, \left[f\,x_{Ik}^{-}, f\,x_{Ik}^{+}\right]\right) = \begin{cases} 1 & if\ \left(f\,x_k \geq f\,x_{Ik}^{-}\ and\ f\,x_k \leq f\,x_{Ik}^{+}\right) \\ \max\left(\dfrac{1}{1+\left|f\,x_k - f\,x_{Ik}^{-}\right|}, \dfrac{1}{1+\left|f\,x_k - f\,x_{Ik}^{+}\right|}\right) & otherwise \end{cases} \qquad (42)$$

When $f\,x_k$ lies between the interval, the similarity value will be 1. Otherwise, the similarity value depends on the extent to which the $f\,x_k$ value is closer to either lower limit $f\,x_{Ik}^{-}$ or the upper limit $f\,x_{Ik}^{+}$. The similarity between the probe gait and reference gait of all the subjects S_I $(I = 1,2,..,N)$ in the knowledge-base is computed and is used at the time of identification as discussed in section 4.

4. EXPERIMENTS

In order to study the performance of the proposed method of gait recognition, two experiments were carried out in this work. In the first experiment, training set is composed of a mixture of gait sequences under different covariate conditions. In the second experiment, the training set contains gait sequences of subjects walking under similar covariate conditions. The gait silhouettes used are in 90 degree (side view) viewing angle as this view provides more gait information than the silhouettes taken from other view angles.

4.1. Datasets used in the experiments

We have conducted experiments on the standard CASIA B dataset [22] and on our newly created University of Mysore (UOM) gait dataset. The CASIA dataset consists of 124 individuals (subjects) with three covariates such as view angle, carrying condition and wearing coat. Each subject consists of 10 series, out of which 2 series are walking sequences carrying a bag, 2 series are walking sequences wearing different clothes and 6 series are in normal conditions.

Due to unavailability of other standard data sets (except CASIA) for us, we created UOM gait dataset to check the efficacy of the proposed system with more covariates. The UOM dataset consists of 66 subjects of 8 sequences per subject captured in 90^0 (side) view with six covariates such as surface, foot wear, carrying bag, holding an object, cloth change and elapsed time. Among 66 subjects, 41 are male and 14 are female subjects. A male subject walking holding an object like water bottle or a female subject walking holding a purse is a new covariate introduced newly by us in the UOM gait dataset and is realistic in real world scenario. Each subject includes all the six covariates and consists of 8 series, out of which 4 series are normal walking, 2 series carrying a bag and 2 series holding an object. The UOM dataset contains a total of 528 sequences of 66 subjects.

We have measured the performance of the proposed gait recognition system using cumulative match scores (CMS) suggested in [23]. The task of recognition is to identify a given probe gait to be one of the reference gait.

4.2. Experimental results on CASIA B database

4.2.1. Experiment I

In this experiment, first series of carrying a bag named as B1 (bag1), first series of coat named as C1 (cloth1) and first three different normal walking series named as N1 (normal1), N2 (normal2) and N3 (normal3) are used for training. Second series of carrying a bag named as B2 (bag2), second series of coat named as C2 (cloth2) and rest of the series of normal walking are named as N4 (normal4), N5 (normal5) and N6 (normal6) are used for testing. Table 4 shows the identification rate of the proposed methodology at rank 1, 5 and 10. The Cumulative Match curve for the proposed system in Fig. 3 shows that the performance at rank 1 is the correct classification rate (CCR) and we have achieved average CCR of 88.99%.

Table 4. Identification rates at different ranks in the proposed approach.

Probe	**Identification rate/Rank (%)**		
	1	5	10
N4	93.33	100.00	100.00
N5	94.16	100.00	100.00
N6	91.66	100.00	100.00
C2	83.33	92.50	98.33
B2	82.50	90.80	97.50
Average CCR	**88.99**		

4.2.2. Experiment II

In the second experiment, only first four different normal walking series named as N1 (normal1), N2 (normal2), N3 (normal3) and N4 (normal4) are used for training. Other two series of carrying a bag named as B1 (bag1), B2 (bag2), two series of coat named as C1 (cloth1) and C2 (cloth2) and last two different normal walking series named as N5 (normal5), and N6 (normal6) are used for testing. Table 5 shows the identification rate of the proposed methodology at rank 1, 5 and 10. The Cumulative Match curve for the proposed system in Fig. 4 shows that the performance at rank 1 is the correct classification rate (CCR) and we have achieved average CCR of 79.01%.

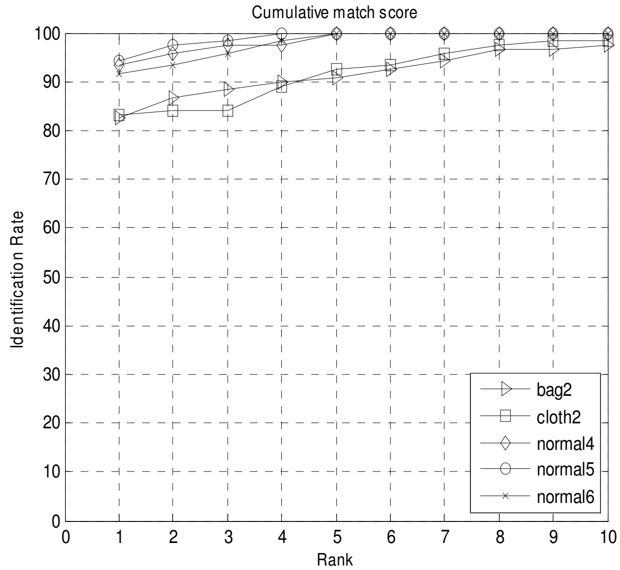


Figure 3. Cumulative Match score

Table 5. Identification rates at different ranks in the proposed approach.

Probe	Identification rate/Rank (%)		
	1	5	10
N5	96.66	100.00	100.00
N6	95.83	100.00	100.00
C1	65.80	71.60	79.16
C2	68.30	74.16	78.30
B1	73.33	79.16	85.80
B2	74.16	80.00	88.30
Average CCR	**79.01**		

Table 6 shows the recognition performance (% of average correct classification rate at rank 1) of experiment I and experiment II as discussed in sub section 4.2.1 and 4.2.2 respectively of the proposed method and other methods reported in [6] and [3].

Table 6. Average CCR of other method and proposed method for side view (90^0)

Approaches	Average CCR (%)	Database
Y. Dupuis [6]	78.8	CASIA B
Jeevan [3]	70.24	
Proposed method exp I	**88.99**	
Proposed method exp II	**79.01**	

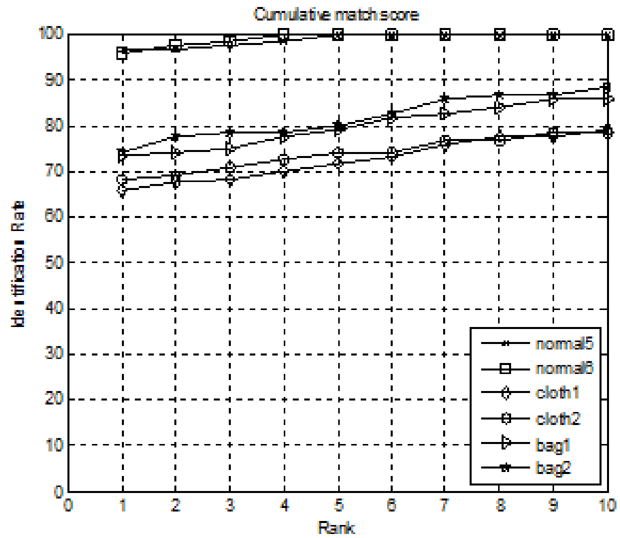


Figure 4. Cumulative Match score

4.3. Experimental results on UOM database

4.3.1. Experiment I

In the first experiment, first series of carrying a bag named as B1 (bag1), first series of holding an object named as O1 (object1), first series of normal walking named as N1 (normal1), and third series of normal walking named as N3 (normal3) are used for training. Second series of carrying a bag named as B2 (bag2), second series holding an object named as O2 (object2), second series of normal walking named as N2 (normal2), and fourth series of normal walking named as N4 (normal4) are used for testing. Table 7 shows the identification rate of the proposed methodology at rank 1, 5 and 10. The Cumulative Match curve for the proposed system in Fig. 5 shows that the performance at rank 1 is the correct classification rate (CCR) and we have achieved average CCR of 92.79%.

Table 7. Identification rates at different ranks in the proposed approach.

Probe	**Identification rate/Rank (%)**		
	1	5	10
N2	95.45	98.48	100.00
N4	98.48	100	100.00
O2	90.90	93.93	98.48
B2	86.36	90.90	95.45
Average CCR	**92.79**		

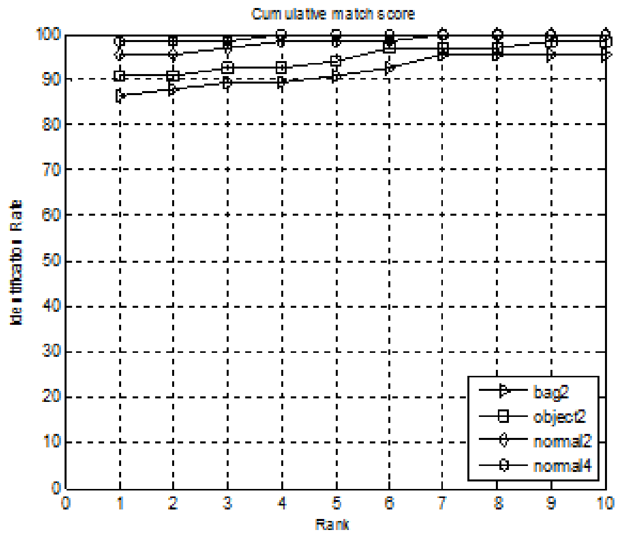


Figure 5. Cumulative Match score

4.3.2. Experiment II

In this experiment, first series of normal walking named as N1 (normal1) and third series of normal walking named as N3 (normal3) are used for training. First series of carrying a bag named as B1 (bag1), second series of carrying a bag named as B2 (bag2), first series of holding an object as O1 (object1), second series holding an object named as O2 (object2), second series of normal walking named as N2 (normal2), and fourth series of normal walking named as N4 (normal4) are used for testing. Table 8 shows the identification rate of the proposed methodology at rank 1, 5 and 10. The Cumulative Match curve for the proposed system in Fig. 6 shows that the performance at rank 1 is the correct classification rate (CCR) and we have achieved average CCR of 86.35%.

Table 8. Identification rates at different ranks in the proposed approach.

Probe	**Identification rate/Rank (%)**		
	1	5	10
N2	98.48	100.00	100.00
N4	96.96	100.00	100.00
O1	81.81	84.84	93.93
O2	84.84	87.87	95.45
B1	78.78	83.33	92.42
B2	77.27	80.30	89.39
Average CCR	**86.35**		

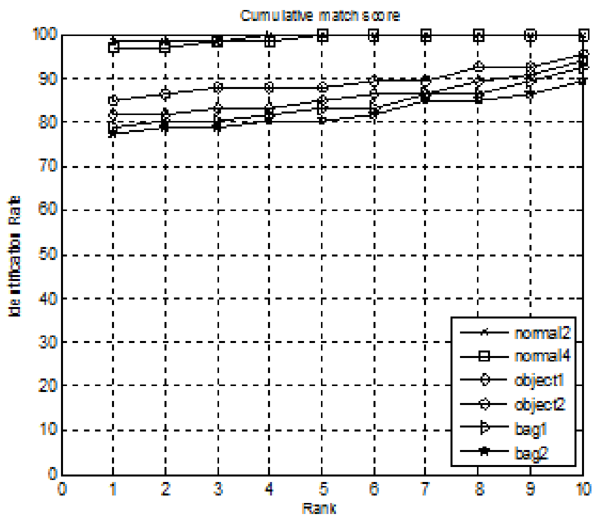


Figure 6. Cumulative Match score

5. Discussion And Conclusion

We have conducted two experiments on both CASIA B and UOM data sets. In the first experiment on CASIA B data set, the proposed gait recognition system has achieved 88.99% of average correct classification rate (ACCR) and in the second experiment, 79.01% of ACCR is reported. A significant difference in the percentage of ACCR is observed in these experiments. In the first experiment, all the covariates of a subject such as change in cloth, carrying a bag and different instances of normal walking conditions are considered during training but in the second experiment, only different instances of normal walking conditions are considered during training. In both the cases, the variations are captured in the form of interval valued type symbolic data. Since, all the covariates are considered in the first experiment, the ACCR (88.99%) is high when compared to the ACCR (79.01%) obtained in the second experiment. This clearly shows that it is very much essential to consider all possible covariates of a gait during training and capture the variations effectively to improve the recognition rate. Though, we have considered more covariates for a subject during training, there is only one reference gait information for a particular subject is stored in the knowledge-base and hence the total number of reference gaits is same in both the experiments for CASIA B data set. This is possible because of symbolic representation as discussed earlier. The above argument is also true for UOM data set. Thus, the proposed representation technique is capable of capturing variations without increasing the size of the knowledge-base. Also observe that the ACCR (88.99% for different covariates in training set) and ACCR (79.01% for similar covariates in training set) obtained from the proposed system for CASIA B data set is significantly high when compared to the ACCR (78.80%) reported by Dupuis [6] and ACCR (70.24%) reported by Jeevan [3] for similar covariates in training set for the same data set.

The proposed approach to gait recognition is found to be robust in capturing variations of gait due to different covariates. The concept of GEI has drastically reduced the complexity of algorithm in terms of space and time needed for gait recognition. The idea of extracting LBP features from split GEIs has effectively captures the local variations of gait information. Experiments conducted on two databases of considerably large size show that the proposed method is robust in capturing variations and the results obtained are encouraging and are comparable with one of the contemporary method. Some other challenging issues such as arbitrary viewing angle, unconstrained dress code and environment will be addressed in our future work.

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