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Gait Recognition: An Approach Based on Interval Valued Features

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Abstract—**Gait is one of the biometric traits used to identify an individual by his/her walking style. Gait can be recognized by observing the shape of the body contour variations with time (Spatio-temporal). In this paper, a method of characterizing gait in terms of interval valued type symbolic features is proposed. Axis of least inertia of a shape is exploited to extract symbolic features for gait representation. 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) to study the efficacy of the proposed gait recognition system. The proposed method has shown the significant improvements when compared to the state-of-the-art techniques in gait recognition.**

Keywords- Axis of Least Inertia, CASIA Data Set B, Interval-valued features, Subject (individual person), Symbolic data.

I. INTRODUCTION

Gait Recognition is one of the biometric techniques which has become a recent focus in computer vision. Gait Recognition is a task to identify or verify the individuals by the way they walk [14]. The ability to identify persons at a distance from a camera is a desirable property and is increasingly important for surveillance and other applications [9]. Gait as a biometric source, can be acquired at a distance without the walkers cooperation or knowledge making it important for some early warnings or monitoring applications that need to perform recognition when the person is far away [27, 28]. There is a need of practical system that can support the authentication process by which one has to undergo to access highly secured area [17]. Gait can be used in situations when other biometric traits such as face, iris and finger print information do not have sufficient resolution for recognition. Several researchers have made attempts to come out with efficient and robust techniques to capture and characterize human gait. Few approaches for gait recognition are discussed below.

II. RELATED WORK

In [18], Radon transform of binary silhouettes was introduced. Here the speed is considered to be constant within any specific gait sequence. For each gait sequence, the transformed silhouettes are used for the computation of a template. The set of all templates is subsequently subjected to linear discriminant analysis and subspace projection. Each gait sequence is described using low-dimensional feature vector consisting of selected Radon template coefficients. Given a test feature vector, gait recognition and verification is achieved by appropriately comparing it to feature vectors in a reference gait database.

In [22], a baseline algorithm, which uses spatial-temporal correlation of silhouettes for gait recognition is proposed. The author, conducted 12 experiments on large data sets to examine the effects of five covariates on performance. The five covariates considered are change in viewing angle, change in shoe type, change in walking surface, carrying or not carrying a briefcase and elapsed time between sequences being compared. Identification rates for the 12 experiments range from 78% on the easiest experiment to 3% on the hardest. All five covariates had significant effect on performance, with walking surface and time difference having the greatest impact.

In [1] width of silhouette is considered as a suitable feature for gait recognition. The width of silhouette is the horizontal distance between the leftmost and the rightmost foreground pixels in each row of the silhouette. Experimental study confirmed that the side-view was the optimal one for capturing the gait characteristics. The method is capable of recognizing gait using the frontal-view but with lower accuracy as compared to that of the side-view.

In [23] a new gait signature based on the correlation analysis of the leg motion is proposed for gait recognition. The motion of two legs during the human walking process is one of the most important gait determinants. The experimental results showed that the leg motion was an important gait signature, which can be combined with other signature like Fourier descriptor features to achieve better recognition results.

In [26], side-view detection from random walking paths of a subject is proposed for gait recognition. The gait feature extraction process comprises three steps: gait cycle determination, side-view partitioning and gait feature template construction. The new gait feature, the Shifted Energy image is used for various body-posture during random walking patterns. Experimental result says the method is better to some of the methods mentioned in the paper.

From the literature survey, on gait recognition systems, we understand that several methods have been proposed to effectively capture gait characteristics for its recognition. Also, it is evident that there will be variations on gait features due to change in viewing angle, changes in cloth type, change in walking surface, carrying bag and elapsed time between sequences being compared. This variation can effectively be handled by the use of symbolic data, which are the extensions of classical data types. Symbolic data are more unified by means of relationships and they appear in the form of continuous ratio, discrete absolute interval, multi-valued and also multi-valued with weights [10]. The concept of symbolic data has been extensively studied in the area of cluster analysis [4, 5, 10, 11, 12, 13, 15, 24] and it has been experimentally shown that the approaches based on symbolic data outperforms conventional data analysis approaches [2, 4, 5]. A symbolic approach to shape representation and recognition has been explored in [3] and the concept of symbolic data analysis has also been explored in online signature verification and recognition [7]. It is also observed from the survey that no attempts have been made to explore symbolic approach to gait recognition except the work reported in [16].

With this backdrop, in this paper, we have proposed a symbolic approach to human gait recognition. The approach makes use of the axis of least inertia of a gait silhouette as a reference to extract the features for gait representation. To study the efficacy of the proposed symbolic approach, an experiment is conducted on the standard gait database (CASIA GAIT DATABASE B) of considerable size. The rest of the paper is organized as follows. The proposed method of gait representation and recognition is presented in section III. The experimental results are presented in section IV, followed by conclusion in section V.

III. Proposed Methodology

The proposed method of gait recognition system involves three main phases i.e., feature extraction, representation and similarity computation for recognition. The input to our proposed methodology is a sequence of binary silhouettes of one gait cycle. A gait cycle is a basic unit of gait and it refers to the time interval between successive instances of initial foot-to-floor contact for the same foot [1]. The gait recognition systems proposed in the literature [18] have assumed that the speed within any specific gait sequence is constant. We have also considered this assumption in this work because length of all instances (change in viewing angle, change in cloth type, carrying a bag, change in walking surface) of a subject is constant. However, speed could vary among reference and probe sequences. Since the gait recognition relies on the shape of the body contour variations with time, we try to capture such variations by extracting features keeping the axis of least inertia of a silhouette as a reference. The axis of least inertia is computed [6, 8] for each silhouette in a gait cycle. The axis is found to be unique to a particular silhouette and thus it is used to extract discriminative features from a gait silhouette. Few silhouettes in a gait sequence of a subject with axis of least inertia is shown in Fig 1.

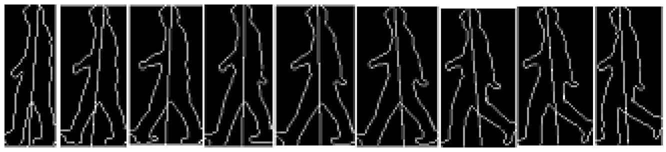

Fig. 1. Sequence of Silhouettes with axis of least inertia

A. Feature Extraction

Extracting relevant features for characterizing a gait is an important step in any gait recognition system. Fig 2 shows an example of silhouette with axis of least inertia as a reference line and the points considered for feature extraction. The features choosen are the distance between centroid C and E1 (*d1*), distance between centroid C and E2 (*d2*), horizontal distance between left boundary point L on the silhouette and centroid C (*d3*), horizontal distance between right boundary point R on the silhouette and centroid C (*d4*) and slope of axis of least inertia (θ). The features listed above are extracted for each t^{th} silhouette in a gait cycle. The gait of a person may vary slightly due to change in clothes, shoes, walking surface, or due to carrying conditions. Such variations can effectively be handled by consolidating the features in the form of an interval type data. Therefore, the features discussed above are extracted from the gait of a person of all instances (change in clothes, due to carrying conditions and different normal conditions) and the features corresponds to a particular silhouette of all instances are consolidated to form an interval. Thus the gait information of a particular person is effectively represented as interval-valued type feature vector in the knowledge-base, which is used at the time of gait recognition.

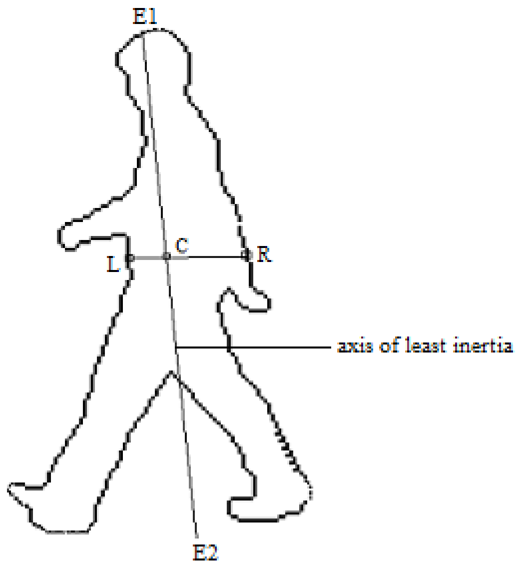

Fig. 2. Silhouette with axis of least inertia and reference points for features extraction

B. Representation

Effective representation of the extracted features makes the recognition system more robust and effective. Since the gait of a person varies at various instances, a gait database generally consists of gait sequences captured in different angles of a same subject in different instances like carrying a bag, wearing different clothes, different normal conditions etc. Fig 3 shows the t^{th} silhouette of a subject at various instances.

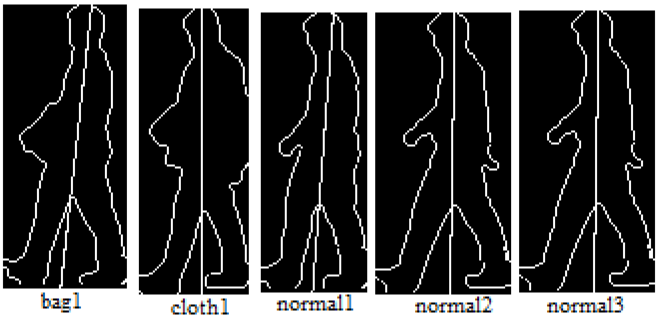

Fig. 3. Particular silhouette of a subject at various instances

Hence gait features corresponds to a particular silhouette of an individual subject have considerable intra subject variations due to different instances. Thus, we propose to have an effective representation to capture these variations by the use of interval valued type feature vector called symbolic feature vector as follows.

Let $S = [S_1, S_2, \ldots\ldots S_I, \ldots\ldots\ldots S_N]$ (1)

be the N number of subjects.

Let $S_I = [s_{I1}, s_{I2}, \ldots. s_{Ii}, \ldots\ldots s_{In}]$ (2)

be the n instances (change in clothes, due to carrying conditions and different normal conditions) of the subject S_I. Let T_{Ii} be the length (i.e., total number of silhouettes in a gait cycle) of s_{Ii}. T_{Ii} is same for all s_{Ii} (i = 1,2,….n) but T_{Ii} could vary at inter subjects, i.e., for different S_I (I = 1,2,…N). Let m be the number of features extracted from t^{th} silhouette of an instance s_{Ii} of subject S_I and is given by

$$s_{Ii}(t) = [f_{Ii1}(t), f_{Ii2}(t), \ldots\ldots\ldots. f_{Iim}(t)] \quad (3)$$

The vector representing the features of all the T_{Ii} silhouettes of s_{Ii} is given by

$$s_{Ii} = [T_{Ii}, F_{Ii1}, F_{Ii2}, \ldots. F_{Iit}, \ldots\ldots. F_{IiT}] \quad (4)$$

where $F_{Iit} = s_{Ii}(t)$ and T_{Ii} is the number of silhouettes of s_{Ii}. The minimum and maximum value of the k^{th} feature of t^{th} silhouettes of all the instances of S_I is given by

$$f_{Ik}^{-}(t) = \min\left(f_{I1k}(t), f_{I2k}(t), \ldots\ldots. f_{Iik}(t), \ldots\ldots.. f_{Ink}(t)\right) \quad (5)$$

$$f_{Ik}^{+}(t) = \max\left(f_{I1k}(t), f_{I2k}(t), \ldots\ldots. f_{Iik}(t), \ldots\ldots.. f_{Ink}(t)\right) \quad (6)$$

The Reference sequence of a subject S_I (I = 1,2,..N) in the knowledge base is thus represented in the form of an interval-valued type symbolic feature vectors as

$$S_I = [T_I, F_{I1}, F_{I2}, \ldots. F_{It}, \ldots\ldots. F_{IT}] \quad (7)$$

Where T_I is the number of silhouettes of a subject S_I and

$$F_{It} = [f_{I1}^{-}(t), f_{I1}^{+}(t)], [f_{I2}^{-}(t), f_{I2}^{+}(t)], \ldots, [f_{Ik}^{-}(t), f_{Ik}^{+}(t)], \ldots. [f_{Im}^{-}(t), f_{Im}^{+}(t)] \quad (8)$$

Where each k^{th} feature $f_{Ik}^{-}(t)$ and $f_{Ik}^{+}(t)$ are obtained as shown in (5) and (6) respectively.

The probe sequence of an instance of subject S_I with m features to be tested is represented as crisp feature vector and is denoted as s_p and given by

$$s_p = [T_P, PF_1, PF_2, \ldots\ldots PF_t, \ldots\ldots PF_T] \quad (9)$$

where T_P is the length of probe sequence (total number of silhouettes in a gait cycle of probe sequence) and

$$PF_t = [f_1(t), f_2(t), \ldots\ldots, f_k(t), \ldots f_m(t)] \quad (10)$$

Table I shows the features representing the t^{th} silhouette of different instances of a subject S_I and the interval-valued representation after consolidating the corresponding features from all instances.

Table I. EXAMPLE OF CRISP FEATURE VALUES AND THE CORRESPONDING CONSOLIDATED INTERVAL-VALUED FEATURES REPRESENTING A PARTICULAR SILHOUETTE OF A SUBJECT

Instances	***d1***	***d2***	***θ***	***d3***	***d4***
Bag1	41.0122	36.0012	0.829	9	8
Cloth1	35.0143	33.0151	0.927	10	13
Normal1	37.0136	35.0176	0.982	7	10
Normal2	39.0157	36.0139	0.936	8	12
Normal3	36.0129	36.0013	0.978	7	11
Interval type values	[35.0143, 41.0122]	[33.0151, 36.0139]	[0.829, 0.982]	[7,10]	[8,13]

C. Similarity computation

In order to recognize a probe sequence s_p, features are extracted from the probe gait sequence as discussed in section *A* and represented as shown in equation (9) of section *B*. The obtained crisp feature vector is compared with the symbolic feature vectors of the reference gait sequences in the gait knowledge-base. Before similarity starts, first the total number of silhouettes T_P in the probe sequence and reference sequence T_I are found. Since the value T_I may vary from subject to subject, there is a possibility that the value T_I (number of silhouettes of reference gait sequence of a subject) and the value T_P (number of silhouettes of a probe gait sequence of a subject) may be different. Suppose if $T_I < T_P$ then, the first T_I silhouettes of a probe sequence of a subject is compared with the reference sequence of a subject and the corresponding similarity value will be computed. If $T_I = T_P$ then the T_I silhouettes of a reference sequence of a subject is compared with the T_P silhouettes of a probe sequence of a subject and the corresponding similarity value will be computed. If $T_I > T_P$, then the first T_P silhouettes of a reference sequence of subject is compared with the probe sequence of a subject and the corresponding similarity value is computed as shown in equation (11). An example of feature vector values (of type crisp) of a t^{th} silhouette of probe sequence s_p is shown in Table II for 5 features. The Similarity measure suggested in [8] is found to suitable and hence is used for computing similarity between reference sequences and probe gait sequence as given in equation (11).

$$TotalSimilarity\left(s_p, S_I\right) = \frac{1}{T}\sum_{I=1}^{N}\sum_{t=1}^{T}\sum_{k=1}^{m} sim\left(f_k(t), \left[f_{Ik}^-(t), f_{Ik}^+(t)\right]\right) \qquad (11)$$

Where

$$sim\left(f_k(t), \left[f_{Ik}^-(t), f_{Ik}^+(t)\right]\right) = \begin{cases} 1 & \text{if } \left(f_k(t) \ge f_{Ik}^-(t) \text{ and } f_k(t) \le f_{Ik}^+\right) \\ \max\left(\dfrac{1}{1+\left|f_k(t)-f_{Ik}^-(t)\right|}, \dfrac{1}{1+\left|f_k(t)-f_{Ik}^+(t)\right|}\right) & \text{otherwise} \end{cases} \qquad (12)$$

When $f_k(t)$ lies within the interval similarity value will be 1 otherwise, similarity value depends on the extent to which the $f_k(t)$ value is closer to either lower limit $f_{Ik}^-(t)$ or the upper limit $f_{Ik}^+(t)$. The similarity between the probe sequence s_p and reference sequence of all the subjects S_I (I = 1,2…N) in the knowledge-base is computed, which is used at the time of identification and is discussed in section IV.

TABLE II. EXAMPLE OF CRISP FEATURE VALUES OF A SILHOUETTE OF PROBE SEQUENCE

Feature No.	***Feature description***	***Feature values of probe sequence (crisp values)***
1	Distance between C and E1 (d1)	36.0183
2	Distance between C and E2 (d2)	35.0198
3	Slope of axis of least inertia (θ)	0.981
4	Distance between L and C (d3)	8
5	Distance between R and C (d4)	10

IV. EXPERIMENTAL RESULTS

In order to study the performance of the proposed method of gait recognition, we have conducted an experiment on the standard CASIA Dataset B. The dataset consists of 124 individuals (subjects). 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. 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 [20, 25]. In the Dataset, some subjects do not have all the series and some of the series do not have a complete gait cycle. Therefore, we have considered only 120 subjects in our experiment out of 124 subjects. We have measured the performance of the proposed approach for identification using cumulative match scores (CMS) suggested in [21].

The task of identification is to identify a given probe sequence to be one of the reference sequence. For identification, 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 and 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. To measure the performance of identification, reference sequences S_I (I = 1,2,…N) are sorted in decreasing order based on the similarity values computed (using equation (11)) with the given probe sequence s_p . If the correct reference sequence has highest similarity value with its corresponding probe sequence, then it is ranked as 1, otherwise its rank will be decided based on its position in the sorted order. We report results in terms of cumulative match scores (CMS).

Table III shows the identification rates of the proposed methodology at various ranks mentioned. Table IV shows the identification rates of the approach reported in [19] at various ranks. The Cumulative Match Score for the proposed system is shown in Fig 4. From Table III and Fig 4, it is observed that set B2 and set C2 have rapid rise in identification rates from rank 2 to rank 5 and reaches maximum within rank 10 in the proposed method. The results obtained shows that the proposed method performs better than the results of [19] shown in table IV from rank 2 to rank 10 in particular for set B2 and set C2.

TABLE III. IDENTIFICATION RATES AT DIFFERENT RANKS

Probe	***Identification rate/Rank (%)***					
	1	**2**	**3**	**4**	**5**	**10**
N4	93.33	97.5	100	100	100	100
N5	96.66	100	100	100	100	100
N6	92.5	95.83	100	100	100	100
B2	76.66	85.83	89.16	90.83	91.66	96.66
C2	79.16	86.66	90	91.66	94.16	97.5

TABLE IV. IDENTIFICATION RATES AT RANKS OF 1,2,5 AND 20

EXP	***Identification rate/Rank (%)***			
	1	**2**	**5**	**20**
Normal	99.2	100	100	100
Clothes	80.6	85.5	92.7	96.0
Bag	75.8	85.5	89.5	95.2

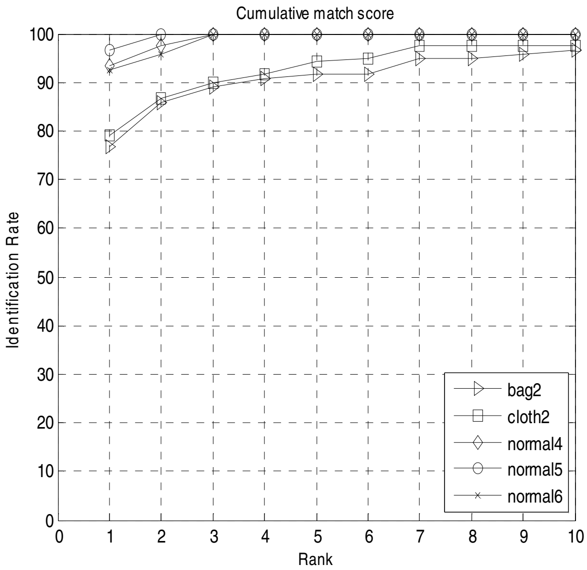

Fig. 4. Cumulative Match Score

V. CONCLUSION

A novel method is proposed for gait recognition. The proposed method makes use of the axis of least inertia of a gait silhouette to extract features. Variations of gait features due to change in cloth, carrying a bag and different normal conditions are captured through interval-valued type symbolic data. Gait recognition is achieved by appropriately comparing crisp values of the probe sequence with interval type values of reference sequences in the gait knowledge-base. The results obtained from our experimentation have shown significant improvement in recognition rate when compared to the contemporary approaches to gait recognition. The other challenging issues related to gait recognition will be addressed in our future work. This paper is expected to open up new applications for gait recognition with the theory of symbolic data analysis.

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