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# Fusion of Silhouette Based Gait Features for Gait Recognition

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*Abstract*— **Identification of person by observing his/her walking style is referred as gait recognition. Gait as a biometric trait finds its applications in various automated controlled environments where authentication of a person at a distance is mandatory as a measure of security. The gait biometric has attracted the attention of computer vision research community from the past two decades. Many researchers have made an attempt to address the issues related to gait biometric and to propose a robust gait recognition system. In this research work, we made an attempt to propose a fusion based gait recognition system, which exploits the fusion of silhouette based gait features extracted from two different feature extraction techniques. An interval value based symbolic representation technique is explored to capture the variations of gait due to different covariates (change in cloth, carrying a bag etc). Extensive experiments are conducted on standard datasets to study the performance of the proposed gait recognition system.**

*Index Terms*— **Axis of Least Inertia, Interval-valued features, Fusion, Subject, Symbolic representation, Matching, Identification.**

## I. INTRODUCTION

With the advance of science and technology, today we are living in the world of automation where most of our day to day activities are controlled and managed by intelligent machines. Any type of automation essentially demand some sort of security due to various types of threats in general. Computer vision plays an important role in many automation systems and, image processing and pattern recognition techniques have become indispensible components in such systems. Automated controlled environments such as banks, parking lots, financial institutions, restricted access locations, airports etc., require authentication of a person in particular as a measure of security. Conventional techniques such as identity cards and smart cards are being used for the purpose of authentication, but with some limitations. In order to overcome the limitations of conventional techniques of authentications, researchers and technicians are exploring efficient and effective techniques for person identification. The concept of biometric has attracted the attention of the researchers as an alternative way to person identification. Many types of biometric traits such as face, fingerprints, palm print, iris, retina, ear, and signature have been explored to provide more robust and accurate recognition of a person. However, there are certain situations where the biometric traits mentioned above are not feasible as they demand person's cooperation, high resolution and other requirements. In such situations gait biometric may be the choice as a supplementary biometric trait. Since gait is an individual style of walking, it can be captured at a distance without regarding to its resolution and cooperation of a person. It has been proved by the research community that the gait of a person is unique and can be used to identify a person at a distance. Identification of a person at a distance in restricted access areas gives the concerned authorities, a time frame to alert and react as a security measure before the person executes a crime, if he happens to be a criminal.

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## II. RELATED WORK

Several attempts have been made by the researchers to provide a more robust and accurate gait recognition system from the past two decades. Some interesting works found in the literature in this direction are discussed below.

AmitKale et al. [1] considered width of the silhouette of the image as features for gait recognition. Hidden Markov model is trained for representation of gait. Their approach has proved that the side-view has higher recognition accuracy compared to the frontal-view. Toby et al. [2] have proposed a method of capturing motion part and static part such as hand, leg and torso respectively through templates called motion silhouette contour templates (MSCT) and static silhouette template (SST). A simple NN classifier is used for classification. Jeevan et al. [3] have proposed temporal representation of Gait using Pal and Pal Entropy. The Principal component analysis was applied to the feature set extracted to create a feature matrix. They have used Support Vector Machine for classification of individuals and demonstrated the experiments on CASIA datasets A, B, C. Pose Energy Image and Pose kinematics features which captures shape and dynamics information respectively was introduced by Aditi Roy et al [4]. PCA and LDA techniques were applied for dimensionality reduction and to extract discriminative features. Optical flow features were considered by Chih-Chang et al. [5] for gait classification. They have considered only optical flow information without shape or other information. Three types of optical flow algorithms such as Lucas-Kanade, Horn-Schunk and Multi-frame are used by them. PCA is used to reduce the dimension of the feature set and simple NN classification technique was used for the task of classification. Experimentations were conducted on CASIA and on their own database. Sadaf Asif et al. [6] have drawn three bounding box around contoured human silhouette. 1) Upper part for arms movement. 2) Middle part for thigh and knee angles. 3) Lower part for legs movement, knee and ankle angles. Thigh, knee, ankle angles and bounding boxes widths are used as gait signatures. SVM based training and identification was performed using the extracted gait features.

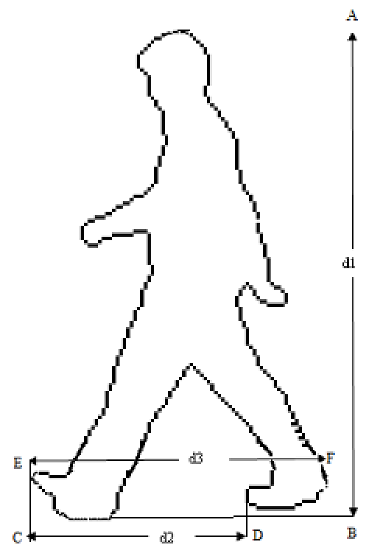
It is evident from the literature that the gait of an individual person varies due to change in cloth, change in shoe, change in surface, carrying a bag etc. Also it has been observed that there will be some variations even in normal walking condition at different point of time. The conventional data 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 [7-12], shape analysis [13] and signature biometric applications [14]. Also suitability of symbolic data analysis approach for gait recognition is attempted recently in [15-18] and in [19] to be published. These unconventional techniques have proved that they outperform the conventional techniques in terms of performance. 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. It is also observed from the literature survey on biometrics that the techniques of feature level fusion and decision level fusion is studied to enhance the performance of the biometric systems. With this backdrop, in this research work, we have proposed the fusion based gait recognition system, which exploits the fusion of silhouette based gait features extracted from two different feature extraction techniques. Performance of the proposed gait recognition system is studied by conducting experiments on the CASIA B gait databases. Rest of the paper is organized as follows. Section III presents proposed methodology for gait recognition. Experimental results are presented in section IV, followed by comparative analysis in section V and conclusion in section VI.

## III. METHODOLOGY

The proposed method of gait recognition system involves three main phases i.e., (i) Fusion of silhouette based gait features extracted from two different feature extraction techniques [15,16]. (ii) Symbolic representation of fused features and (iii) Matching and recognition. Input to our proposed methodology is a sequence of silhouettes of a 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]. We have assumed that the speed is constant within any specific subject gait sequence cycle (length of different instances of a subject like change in viewing angle, change in cloth type, carrying a bag is constant). However, speed could vary among reference (training) and probe (test) sequences. The following subsections provide the detail descriptions about the proposed methodology.

### *A. Method-1: Extraction of direct features*

A gait characteristic depends on the variations in the shape of the body contour overtime and most of the distinguishing information lies in the leg arm region [20-21]. It can be observed from a gait cycle that there will be changes in height, width and in step length of human walk. These variations differ from person to person and found to be unique among different subjects. Therefore, we have extracted three prominent temporal features, such as height, width and step length directly from a silhouette during walk of a subject in one gait cycle. Also, we have considered ratio of height to width as one of the feature. Fig. 1 shows an example of gait silhouette and the features extracted to characterize it. The distance between A and B is considered as height of a gait silhouette and is denoted as d1, similarly, the distance between C and D is considered as step length and is denoted as d2, distance between E and F is considered as width and is denoted as d3. Besides these three features, the ratio of height to width i.e., d1/d2 is also considered as feature and is denoted as d4. Thus the feature vector DF = {d1, d2, d3, d4} of dimension four is used to describe the gait silhouette in this method.




### *B. Method-2: Extraction of indirect features*

In this method, axis of least inertia of a gait silhouette is exploited to extract features to characterize the gait. The shape of a gait silhouette changes during a gait cycle and this changes is captured by the use of axis of least inertia [22]. The orientation of the axis of least inertia depends on the gait silhouette and is found to be unique. Since, the shape of a gait silhouette changes during a gait cycle, the orientation of the axis of least inertia also changes. Thus, the slope angle (θ) of the axis of least inertia of a gait silhouette is considered as one of the prominent feature to characterize the gait. It is also observed that, the length of the axis of least inertia of a gait silhouette and its centroid changes during a gait cycle. Therefore, the distance (D1) between the centroid (C) and the extreme point E1 of the axis of least inertia is computed and considered as a feature value. Similarly the distance (D2) between the centroid (C) and the extreme point E2 of the axis of least inertia, the horizontal distance (D3) between the centroid (C) and the extreme left point on the gait silhouette (L) and the horizontal distance (D4) between the centroid (C) and the extreme right point on the gait silhouette (R) are captured as feature values. Thus, the feature vector IF = {D1, D2, D3, D4, θ} of dimension five is used to characterize the gait silhouette in this method. Fig. 2 shows an example of gait silhouette with axis of least inertia and the points considered to extract the features. Since, the features extracted in this method depends on the axis of least inertia of a gait silhouette, we refer these features as indirect features.

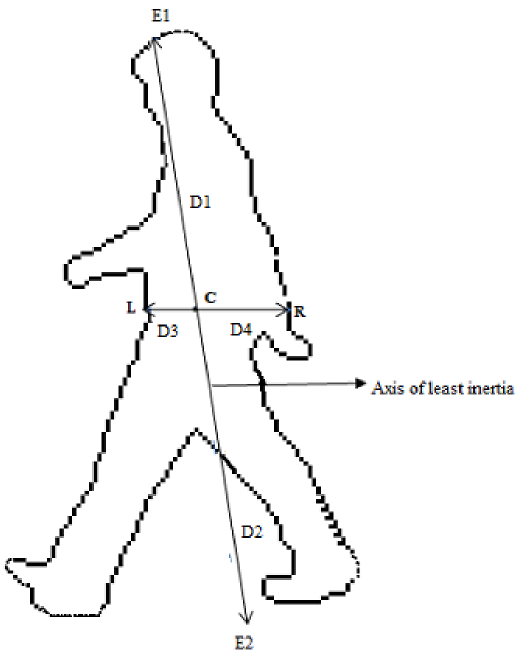



Fig. 2 Silhouette with axis of least inertia

### C. Fusion of gait features

It is quite meaningful to combine the features extracted from two or more different techniques to study the performance of any biometric system. Thus, in this work, we propose to fuse the features extracted from the two methods as described in the previous sections. A simple concatenation operation is performed on the feature vector to produce the combined feature vector. So, in general terms, Let DF = {d1, d2, d3, d4} be the four-dimensional feature vector describing gait silhouette according to method-1 and Let IF = {D1, D2, D3, D4, θ} be the five dimensional feature vector describing gait silhouette according to method-2. The fusion of these two feature vectors is given by FF = {d1, d2, d3, d4, D1, D2, D3, D4, θ} which is of dimension nine. So, to make it more general and convenient for representation, we denote the fused feature vector as F = {f1, f2, f3, . . . . . , fm} where $m$ = 9.

### D. Symbolic Representation of Gait

Effective representation of the extracted features makes the recognition system more robust and effective. Since the gait of a same person varies at various instances (covariates) like carrying a bag, wearing different clothes, different normal conditions etc, and these variations are handled by consolidating the features in the form of an interval type data. Fig. 3 shows the $t^{th}$ silhouette of a subject at various instances (covariates).

Let $S = \{S_1, S_2, \ldots S_I, \ldots\ldots S_N\}$ (1)

be the $N$ number of subjects.

Fig. 3 Silhouettes with different covariates

Let $S_I = \{s_I^1, s_I^2, \cdots, s_I^j, \cdots, s_I^n\}$ (2)

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

$$s_I^j(t) = \{f_{I1}^j(t), f_{I2}^j(t), \ldots\ldots\ldots f_{Im}^j(t)\} \quad (3)$$

Where $t$ denotes the particular gait silhouette in a gait cycle.

The vector representing the features of all the $T_I^j$ silhouettes of $s_I^j$ is given by

$$s_I^j = \{T_I^j, F_{I1}^j, F_{I2}^j, \ldots F_{It}^j, \ldots\ldots F_{IT}^j\} \quad (4)$$

Where $F_{It}^j = s_I^j(t)$ and $T_I^j$ is the number of silhouettes of $s_I^j$. The minimum and maximum value of the $k^{th}$ feature of $t^{th}$ silhouette of all the instance of $S_I$ is given by

$$f_{Ik}^-(t) = \min\left(f_{Ik}^1(t), f_{Ik}^2(t), \ldots\ldots f_{Ik}^j(t), \ldots\ldots f_{Ik}^n(t)\right) \quad (5)$$

$$f_{Ik}^+(t) = \max\left(f_{Ik}^1(t), f_{Ik}^2(t), \ldots\ldots f_{Ik}^j(t), \ldots\ldots f_{Ik}^n(t)\right) \quad (6)$$

The reference sequence of a subject $S_I$ ($I = 1,2,\ldots, N$) 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 $S_I$ of *m* features to be tested is represented as crisp feature vector and is denoted as $S_p$ and given by

$$S_p = \{T_P, PF_1, PF_2, ......PF_t, ......PF_T\} \quad (9)$$

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

$$PF_t = \{f_1(t), f_2(t), ......, f_k(t), ...f_m(t)\} \quad (10)$$

Table I shows the features representing the $t^{th}$ silhouette of different instances (covariates) of a subject $S_I$ and the corresponding symbolic features in interval-valued form. An example of feature vector values (of type crisp) of a $t^{th}$ silhouette of probe sequence $S_p$ is shown in Table II.

### *E. Gait Matching and Recognition*

In order to recognize a probe sequence $S_p$, the features are extracted from the probe gait sequence using the techniques discussed in the section III A and III B. The extracted features are then fused as described in section III C and the fused feature vectors are used to represent the probe gait sequence. It is noticed that the probe gait sequence is represented by a set of crisp feature vectors as the probe gait is in any one of the covariates mentioned earlier. Now, the crisp feature vectors of the probe gait sequence are matched with the symbolic feature vector of the reference gait sequence stored in the gait knowledge base. The Similarity measure proposed in [23] is used to compute similarity between reference sequences and probe gait sequence.

$$TotalSimilarity(S_p, S_I) = \left(\sum_{t=1}^{T}\sum_{k=1}^{m} sim\left(f_k(t), \left[f_{Ik}^{-}(t), f_{Ik}^{+}(t)\right]\right)\right) - \left(\left|T_P - T_I\right|\right) \quad (11)$$

For I = 1 to N

Where

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

When $f_k(t)$ lies between the interval, the 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 $f_{Ik}^{+}(t)$. $\left|T_P - T_I\right|$ is computed and subtracted from total similarity value, when the Probe and reference gait sequence are not equal. 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 IV.

## IV. EXPERIMENTS AND RESULTS

In order to study the performance of the proposed method of gait recognition, four experiments were carried out on CASIA B dataset [24]. The gait silhouettes used are in $90^0$ (side view) viewing angle, as this view provides more gait information than the silhouettes taken from other view angles. The CASIA B 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. We have measured the performance of the proposed approach to gait identification using cumulative match scores (CMS) [25].

Table I : Example of crisp feature values and the corresponding interval-valued features representing $t^{th}$ silhouette in each covariate of a gait cycle of combined features

| ***Covariates*** | ***f1*** | ***f2*** | ***f3*** | ***f4*** | ***f5*** | ***f6*** | ***f7*** | ***f8*** | ***f9*** |
|---|---|---|---|---|---|---|---|---|---|
| Bag1 | 130 | 39 | 69 | 1.88 | 41.01 | 36.00 | 9 | 8 | 0.82 |
| Cloth1 | 131 | 41 | 70 | 1.87 | 35.01 | 33.01 | 10 | 13 | 0.92 |
| Normal1 | 129 | 38 | 69 | 1.86 | 37.01 | 35.01 | 7 | 10 | 0.98 |
| Normal2 | 128 | 40 | 70 | 1.82 | 39.01 | 36.01 | 8 | 12 | 0.93 |
| Normal3 | 130 | 37 | 68 | 1.91 | 36.01 | 36.00 | 7 | 11 | 0.97 |
| Interval type values | [128, 131] | [37, 41] | [68, 70] | 1.82, 1.91] | [35.01, 41.01] | [33.01, 36.01] | [7,10] | [8,13] | [0.82, 0.98] |

Table II : Example of crisp feature values of a silhouette of probe sequence

| ***Feature No.*** | ***Features*** | ***Feature values of probe sequence (crisp values)*** |
|---|---|---|
| 1 | *f1* | 131 |
| 2 | *f2* | 38 |
| 3 | *f3* | 69 |
| 4 | *f4* | 1.89 |
| 5 | *f5* | 36.01 |
| 6 | *f6* | 35.01 |
| 7 | *f7* | 8 |
| 8 | *f8* | 10 |
| 9 | *f9* | 0.98 |

### *A. Experiment I*

In this experiment feature level fusion with the training set composed of different covariates are considered. 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 III 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 88.65%.

Table III : Identification rates at different ranks in the proposed approach

| *Probe* | *Identification rate/Rank (%)* | | |
|---|---|---|---|
| | 1 | 5 | 10 |
| N4 | 94.16 | 100.00 | 100.00 |
| N5 | 96.66 | 100.00 | 100.00 |
| N6 | 93.33 | 100.00 | 100.00 |
| C2 | 80.83 | 96.66 | 98.33 |
| B2 | 78.30 | 91.66 | 96.66 |
| Average CCR | **88.65** | | |

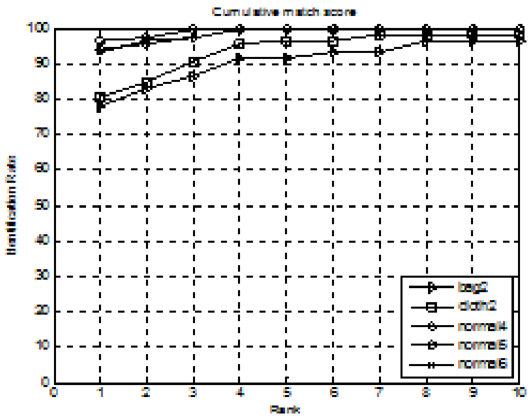



Fig. 4 Cumulative Match Score

## B. *Experiment II*

In this experiment feature level fusion with the training set composed of same covariates such as normal walking are considered. In the 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 IV 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 79.30%.

Table IV : Identification rates at different ranks in the proposed approach

| *Probe* | *Identification rate/Rank (%)* | | |
|---|---|---|---|
| | 1 | 5 | 10 |
| N5 | 97.50 | 100.00 | 100.00 |
| N6 | 95.83 | 100.00 | 100.00 |
| C1 | 69.16 | 78.30 | 86.66 |
| C2 | 64.16 | 71.66 | 80.83 |
| B1 | 76.66 | 83.33 | 90.00 |
| B2 | 72.50 | 79.16 | 90.80 |
| Average CCR | **79.30** | | |

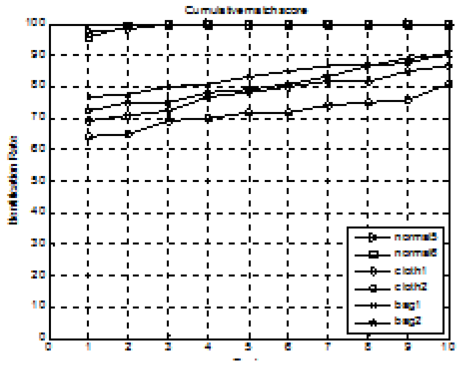



Fig. 5 Cumulative Match Score

## C. *Experiment III*

In this experiment score level fusion with the training set composed of different covariates are considered. The training and testing set is same as in the experiment I. Table V 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 88.99%.

## D. *Experiment IV*

In this experiment score level fusion with the training set composed of same covariates such as normal walking are considered. The training and testing set is same as in the experiment II. Table VI shows the identification rate of the proposed methodology at rank 1, 5 and 10. The Cumulative Match curve for the proposed system in Fig. 7 shows that the performance at rank 1 is the correct classification rate (CCR) and we have achieved average CCR of 79.85%.

Table V : Identification rates at different ranks in the proposed approach

| *Probe* | *Identification rate/Rank (%)* | | |
|---|---|---|---|
| | 1 | 5 | 10 |
| N4 | 94.16 | 100.00 | 100.00 |
| N5 | 96.66 | 100.00 | 100.00 |
| N6 | 93.33 | 100.00 | 100.00 |
| C2 | 80.83 | 95.83 | 99.16 |
| B2 | 80.00 | 93.33 | 98.33 |
| Average CCR | **88.99** | | |

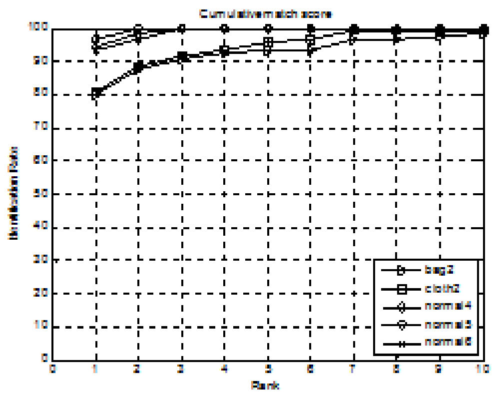



Fig. 6 Cumulative Match Score

Table VI : Identification rates at different ranks in the proposed approach

| *Probe* | *Identification rate/Rank (%)* | | |
|---|---|---|---|
| | 1 | 5 | 10 |
| N5 | 97.50 | 100.00 | 100.00 |
| N6 | 95.83 | 100.00 | 100.00 |
| C1 | 70.80 | 80.00 | 86.66 |
| C2 | 65.00 | 71.66 | 81.66 |
| B1 | 77.50 | 85.00 | 94.16 |
| B2 | 72.50 | 80.00 | 90.80 |
| Average CCR | **79.85** | | |

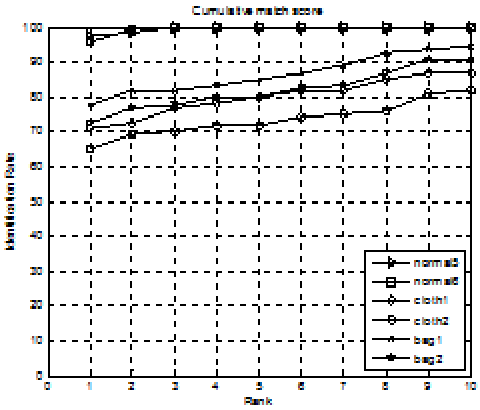



Fig. 7 Cumulative Match Score

## V. COMPARATIVE ANALYSIS

In this section results of method-1, method-2, feature level fusion and score level fusion for training set with different and same covariates is summarized and compared. Table VII is the summary of the results of experiments with training and probe set consisting different covariates. It is noticed that results of fusion at feature level and score level has yielded better average correct classification rate compared to results of method-1 and method-2 without fusion.

Table VII : Experimental results of the proposed approach for different covariates in training set

| **Average CCR** | **Method-1** | **Method-2** | **Feature level Fusion** | **Score level Fusion** |
|---|---|---|---|---|
| | 83.98 | 87.66 | 88.65 | 88.99 |

Table VIII is the summary of the results of experiments with training set consisting same covariates such as normal walking and probe set with different covariates. It is seen from that the results of fusion at feature level and score level has yielded better average correct classification rate compared to results of method-1 and method-2.

Table VIII : Experimental results of the proposed approach for same covariates in training set

| **Average CCR** | **Method-1** | **Method-2** | **Feature level Fusion** | **Score level Fusion** |
|---|---|---|---|---|
| | 74.02 | 78.47 | 79.30 | 79.85 |

The advantage of our proposed approach with symbolic representation in gait recognition is that, the storage space for the knowledge base remains same and does not change either for training set with same or different covariates for given number of subjects. Also, the time required in retrieving the data from the knowledge base during matching of training set (same or different covariates) with different probe set remains same and does not change (except with increase of subjects in the database). Thus the symbolic approach way of representing data in the interval form in the knowledge base reduces the storage and time complexity and increases the rate of recognition.

## VI. CONCLUSION

In this paper, performance of the feature level and decision level fusion strategy for gait recognition is studied. Silhouette based gait features extracted from two different techniques are fused. Effectiveness of different covariates and similar covariates at the time of training is demonstrated. Efficiency of interval value based symbolic representation technique is assessed. Experimental results conducted on the CASIA B data set have proved that the proposed fusion strategy has yielded significant improvement in the overall recognition rate.

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