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Analysis of Spatio-Temporal Dynamic Patterns of Gait for Recognition

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***Abstract*— This work presents a five-phase automatic gait recognition method that analyzes the spatiotemporal shape and dynamic motion (STS-DM) characteristics of a human subject's silhouette to identify the subject in the presence of many challenging factors that affect gait. Phase-1 describes Krawtchouk Moments for feature extraction; phase-2 describes phase weighted magnitude spectra of the Fourier descriptor of a silhouette. Phase-3 gives a full body shape and motion analysis using ellipses. In Phase-4, dynamic time warping is used to analyze thigh angle rotation pattern. In phase-5 DHT based height varying signal pattern is analyzed. Five phases are fused to give a robust identification system.**

Keywords— Krawtchouk Moments; STS-DM;DTW; DHT

I. INTRODUCTION

In surveillance systems, human identification is a challenging job. Human identification uses biometric recourses, such as fingerprint, palm print, face, iris, hand geometry, etc [1, 2]. The biometric features of a face will not give satisfactory result when the distance between the camera and person is large. In such case, gait features will give an estimable result. Human gait recognition works from the observation that an individual's walking style is unique and can be used for human identification at low resolution without interfering with the subject's activity. Therefore it can be used in situations where other physiological biometrics, e.g., face, fingerprint or iris information are not available in high enough resolution for recognition [1]. There is an increased interest in gait identification system due to its non-invasive, nonintrusive and without subject's cooperation [3]. However, variations of the subject's clothes, footwear and hair style, variation in viewpoint, walking speed, and shape distortions due to carrying conditions add complexity to gait recognition. Thus, a robust gait recognition method needs to analyze bio mechanical gait characteristics of silhouette via static and dynamic pose changes of gait [7].

There have been many works on human recognition through gait which can be divided into three distinct groups. Wearable Sensor-based (WS), Floor sensor based (FS), Machine vision based (MV) gait recognition techniques [3]. However, the first two approaches require subject's cooperation. So it is only applicable to clinical aspects of the system [12, 13]. Machine vision (MV) based gait recognition further divided into feature based (silhouette based) and model based. Silhouette-based approaches aim to extract statistical subject's silhouette to differentiate between subjects [2]. The disadvantage of above approaches is that they ignore the temporal components of gait. The method in [2] which employees a probabilistic sub-gait interpersonal model to analyze sub-gaits, i.e., different parts of silhouette, uses Bayesian networks, but it requires a priori knowledge of gait-parameters distribution. The structural model represents the subject by a stick figure / ellipsoidal fits / a volumetric model based on proportions of the human body parts, and measures time-varying gait signatures [6]. The motion model is used to analyze kinematical and dynamical motion parameters of the subject, e.g., rotation pattern of hip and thigh, joint angles and orientation change of limbs [9, 10]. The popular shape descriptors used to analyze static shape characteristics using Fourier Descriptors [11]. Spatio-temporal deformation of the subject's shape in a gait sequence provides better discriminative power than its kinematics; inclusion of dynamical motion characteristics improves the identification rate [11]. Thus, the spatiotemporal shape features of a subject's silhouette period using both model-free and model-based approaches to achieve robustness of the gait recognition system. To challenge on clothing style, the method uses appearance and dynamic traits of gait by analyzing parameters of the ellipse fitted to five regions of a subject's silhouette along with the subject's height variation pattern for identification which is invariant to limited clothing variations and segmentation imperfection. To challenge on carrying condition, it introduces a component-based Fourier descriptor (FD) that measures from head to shoulder part which is not affected due to carrying an object. Carrying a bag or small item with folded arms by a subject can be detected by analyzing the difference in the number of contour points enclosed in the region bounded by the top of the bounding rectangle. Apart from that Krawtchouk moments using Euclidian distance [8] and Thigh angle rotation pattern using DTW are proposed for feature extraction due to its high discriminative power [7]. Krawtchouk moment is used for reconstruction of the original image using relatively low-order moments. By using theses Krawtchouk moments, the recognition performance of our proposed algorithm on the Gait-challenge database [5] is seen to improve over the methods in [12, 13].

The layout of this paper is as follows. Section II describes the overview of the proposed method. Experimental setup and results are shown in Section III, and the paper is concluded in section IV.

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II. Overview of the Proposed Method

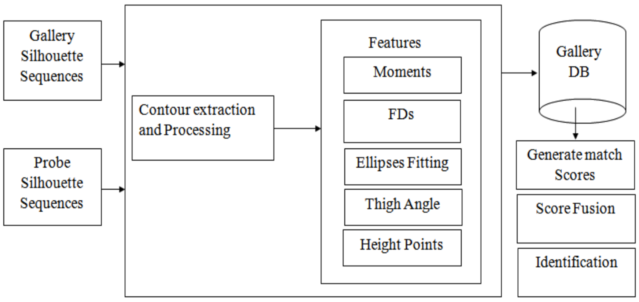

Figure. 1. Overview of STS-DM.

Spatiotemporal Shape and Dynamic Motion (STS-DM) analysis, comprises five phases of gait feature extraction as shown in Fig. 1. The preprocessing stage includes silhouette extraction using background subtraction methods and contour extraction using canny edge detection method. Each phase generates a match score. Then the matched scores are fused using weighted-based score-level fusion for subject identification.

- Phase 1: Feature Extraction using Krawtchouk moments (KR)

The Krawtchouk polynomial is the orthogonal polynomial w.r.t. the binomial distribution. The Krawtchouk moments of order (n+m) in terms of weighted Krawtchouk polynomials for an image intensity function $f(x,y)$ is defined as

$$Q_{nm} = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1} \bar{K}_n(x;p1,N-1)\cdot \bar{K}_m(y;p2,M-1)\cdot f(x,y). \quad (1)$$

$N \times M$ are the pixel points of an image. The Krawtchouk moments are the inner product of $f(x,y)$ and $\bar{K}_n(x;p_1,N-1)$, $\bar{K}_m(y;p_2,M-1)$.

The reconstructed image can be obtained by using the following inverse moment transform.

$$f(x,y) = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1} Q_{nm}\, \bar{K}_n(x;p_1,N-1)\times \bar{K}_m(y;p_2,M-1) \quad (2)$$

Autocorrelation algorithm exploits periodic signal of gait to get gait cycle. The gait cycle contains 10 key phases of gait. The weighted Krawtchouk moments (1) are computed for each phases of subjects of gallery and probe set. N and M are width and height of the scaled and aligned silhouette of each sequence respectively. To obtain similarity scores between gallery and probe, Euclidian distance metric between moments have been computed.

- Phase 2: Feature Extraction using Phase Weighted Magnitude Spectrum (PWMS)

Fourier descriptor (FD) represents the shape of the contour in frequency domain and reconstructs the shape of the contour and thus it is a useful boundary shape descriptor for object recognition. Its low–frequency FDs contain global shape characteristics and the higher frequency FDs substantiates the discrimination between different shapes. The magnitude spectrum is multiplied by its corresponding phase of FDs to generate PWMS. PWMS are represented as $o \times k$ matrix, where o represents the number of frames in a gait cycle (typically, o=10) and k is the number of spectral points taken along the contour of the sub sampled foreground subject (typically k=128). Let A and B be two such matrices for a gallery and a probe gait sequences, respectively. The dissimilarity score between them is

$$d_{pwms} = \frac{\sum_{i=1}^{o}\sum_{j=1}^{k}(A_{i,j}-B_{i,j})^2}{\sum_{j=1}^{k}(\sum_{i=1}^{o}(A_{i,j}-mean(A_j))^2)}, \quad (3)$$

where A_j is the j-th column vector of A, and mean (A) computes the average of the column vectors of A. The range of d_{pwms} is [0 1], the smaller the value the more similar are the two shapes.

- Phase 3: Analysis of full-body shape motion by an ellipse using Histogram (BDHM)

The Silhouette is divided into five regions with each region fitted with an ellipse as shown in fig. 2. An ellipse is preferred over a circle and a rectangle as it has more useful parameters to describe shape characteristics (i.e., aspect ratio, area and eccentricity) and motion characteristics (i. e orientation angle, the angle of the semi major axis of the ellipse measured anti-clock-wise from positive horizontal axis). We compute 1-D histograms for each of the parameters of an ellipse for a ten phase gait period. The normalized histograms of the probe gait sequences (Hist-pn, n = 1, . . ., 20) are compared with the corresponding histograms of the gallery sequences (Hist-gn) using Bhattacharyya distance metric to obtain the dissimilarity score [11], given by:

Figure. 2. Ellipses are fitted to each of the five segments of a subject.

$$d_n(Hist-p_n, Hist-g_n) = \left(1-\sum_{i}^{B}\frac{\sqrt{Hist-p_n(i).Hist-g_n(i)}}{\sqrt{\sum_i Hist-p_n(i).\sum_i Hist-g_n(i)}}\right)^{\frac{1}{2}} \quad (4)$$

The gait signature is the average dissimilarity score. $d_{BDHM} = \frac{1}{20}\sum_{n=1}^{20} d_n$, The range of d_{BDHM} is [0, 1], and the low values of d_{BDHM} indicate good matches.

- Phase 4: Feature extraction from Thigh angle Rotation Pattern using Dynamic Time Warping (DTW).

The Model based approach uses a model of either the person's shape (structure) or motion, in order to calculate thigh angle with respect to horizontal line as shown in Fig. 3 and 4. Here the gait cycle is used to detect the thigh angle when one leg is occluded by other leg. A procedure for getting thigh points is given bellow

- Lower point (feet point) and upper point (head point) is detected using corner detection technique.
- Height detection using calibration process.
- Canny edge detector is used to detect the edges.
- Thigh point = calibrated height * 0.53
- Edge linking method is applied using local processing and region processing. First requires knowledge about edge points in the local region (3×3 or 5×5 neighborhood).The second requires that points on the boundary of a region be known.
- The second point in the thigh is known by using the (3×3 or 5×5 neighborhood) whose weight is equal to '1'.

All the points which are passing through above two points are the thigh points and can be calculated using straight line equation.

- Calculate the thigh angle with respect to horizontal line.

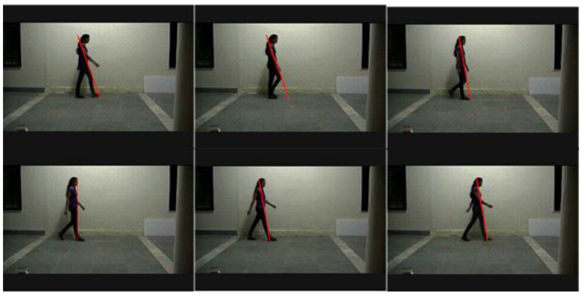

Figure. 3. Thigh line is shown on the sequence of database

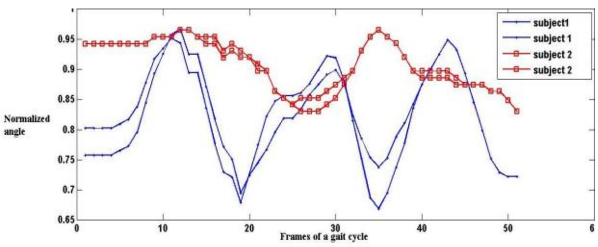

Figure 4. Variation of thigh angle with respect to horizontal line. X-axis represents number of frames and y-axis represents angles.

Different subjects have different walking speeds which result in varying number of frames in their gait period. So DTW uses dynamic programming to compute a warping function that optimally aligns two time-dependent sequences of varying angles to measure similarity.

- Phase 5: Feature extraction using Height variation Pattern (HP)

Corner points are detected after detection of silhouette, using Plessey corner detector as shown in Fig. 4. This operator considers a local window in the image and determines the average change of intensity resulting from shifting the window by a small amount in various directions. This operation is repeated for each pixel position which is assigned an interest value equal to the minimum change produced by these shifts. Points of interest are the local maximum of the interest values since corners exhibit a large intensity variation in every direction. Once the corner points are detected, then the top max point and bottom min point of the silhouette are selected. These points are called head and feet point respectively.

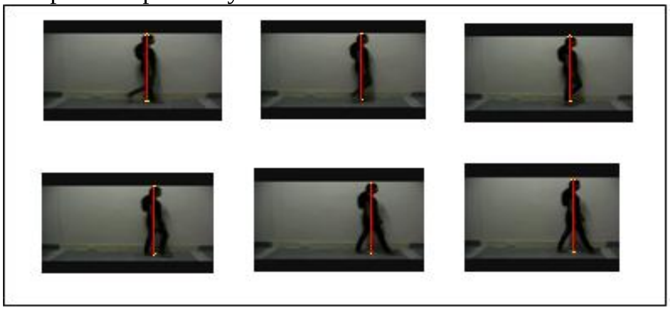

Figure 5. Walking sequence with extracted height model for a subject. Frames run from left to right.In the swing phase (one feet is in the ground and other feet toe-off) the vertical segment between the head and feet and the height is maximum. In stance phase (when two feet contact in the ground and apart) the vertical segment that extends from the top of the head to the point halfway between the two feet. At that time height is the minimum.

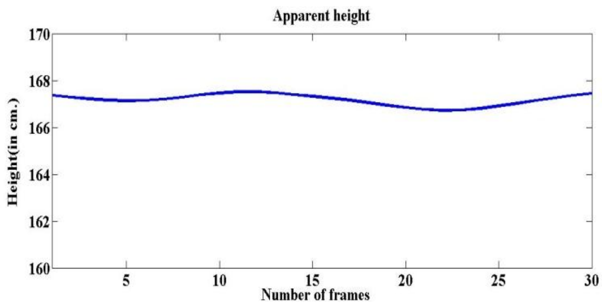

Figure. 6. Height changing pattern extracted with the height model for the sequence in fig. 5.

1-D height signal is generated by combining the height of each frame in a gait period. Different windowing techniques such as Blackman window and Rectangular window are applied to get finite samples from this continuous signal. Windowing techniques are applied to avoid leakage outside the finite interval. Discrete Hartley Transformation [6] is used on the samples to get features.

To identify each subject, a distance metric between the probe and gallery sequence is obtained (5) for match score S , where S is either KR, PWMS, BDHT, DTW or DHT. k is the kth probe gait period. i is the number of gallery gait periods in a gallery sequences.

$$Dist_S(k) = \min_i(S) \quad (5)$$

Z-Score normalization is used to normalize each match scores. The fused score is obtained using (6)

$$s_f = \frac{I_{KR} \times Z_{KR} + I_{PWMS} \times Z_{PWMS} + I_{HP} \times Z_{HP} + I_{DTW} \times Z_{DTW} + I_{BDHM} \times Z_{BDHM}}{I_{KR} + I_{PWMS} + I_{HP} + I_{DTW} + I_{BDHM}} \quad (6)$$

where s_f is fused score, Z is the normalized z-score classifier of five phases. The probe subject is identified based on the lowest s_f it measures with the number of a gallery class.

III. EXPERIMENTAL SET UP AND RESULTS

The combination of model free and model based methods in terms of STS-DM provides robustness against most challenging factors of gait recognition. It evaluates using CASIA gait dataset [7] with 25 subjects walking with two different speeds (2mph and 3mph) as well as some manually capture data sets of 15 subjects at 30fps in two days gap. The identification is best interpreted by a cumulative match characteristic curve (CMC) which shows correct classification rate (CCR) at different ranks. The smaller the value of match scores, more similar is the two subjects. CCR for KR, PWMS, HP, DTW, BDHM are 93%, 88%, 86%, 84%, 74% respectively as shown in Fig. 8. It is clear from Fig.10 that STS-DM outperforms all other methods and provides rank1 identification rate.

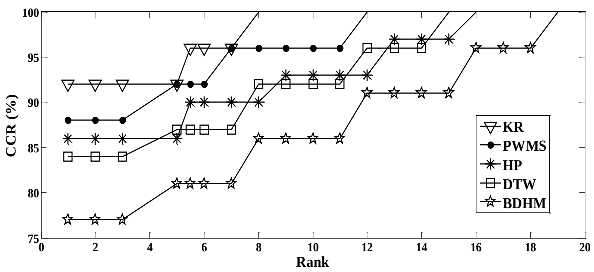

Figure. 7. CMC curves of classification rates obtained using KR, PWMS,HP,DTW and BDHM of the lateral-view silhouette from CASIA dataset.

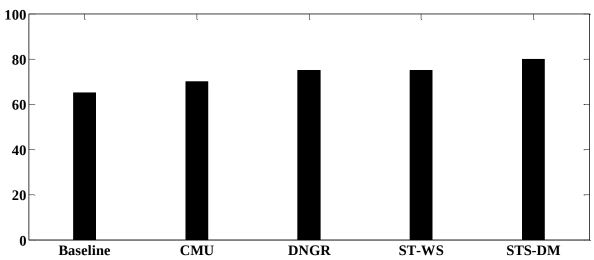

Figure. 8. Identification rate Comparison with related works.

IV. CONCLUSION

In this work, a novel gait recognition methodology has been presented based on five feature descriptors which give a matching score between probe and gallery subjects. A shadow free silhouette is constructed using fuzzy rule based method, which improves the recognition performance in dynamic illumination conditions. The proposed system has been evaluated with the use of KR, PWMS, HP, DTW, and BDHM as feature extraction for identification and verification purpose. Comparing individual features, KR gives good detection scheme. By fusing the features, the recognition performance of the proposed methodology has been improved compared to other methodologies.

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