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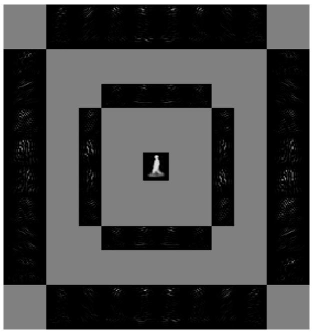
Gait recognition using GEI and curvelet



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Abstract: Gait energy image (GEI) is composed of static body silhouette and dynamic frequency information of human gait. To achieve fast and efficient gait recognition, combined with the accurate description of the information of details and directions in image by Curvelet transform, a gait recognition method using GEI and Curvelet (GEIC) is presented. Firstly, to gain the gait energy images, the gait cycle is selected according to the aspect ratio. Secondly, Curvelet energy coefficients of the GEI, which are used as gait feature vector, are extracted by Curvelet transform in different scales and different directions. Finally, the gait recognition is accomplished by the K nearest neighbor (KNN) classifier. The experimental results demonstrate that GEIC performs well on CASIA(B) database, with the average accuracy of 86.83%. Compared with GEI+KPCA, GEI+W(2D)2PCA and GEI+(2D)^{2}PCA, the algorithm GEIC achieves better robustness in the condition of the person wearing or packaging.

Keywords: gait recognition; GEI; curvelet decomposition; curvelet feature extraction; KNN

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1 Introduction

Recently, international and domestic academics are attracted by biometric feature's recognition, because the intelligent monitoring, which is the basis of social security, is more required by people. Compared with other biometric features (face, iris fingerprint and so on), gait feature has its advantages, such as acceptability, noninvasiveness, hard to hide and easy to be collected. At present, there are various algorithms available for human gait representation, which can be roughly divided into two categories: model-based [1] and silhouette-based [2-3] algorithms. Model-based algorithm is that the model of human body is built to extract the body structure parameters which are used as gait features to accomplish the recognition from the original gait sequence. Zeng [4] et al proposed a new dynamical pattern recognition method via the deterministic learning theory. Lower limb joint angle and angular velocity state vectors are extracted from side silhouette, which is based on the five-link biped del were characterized as the gait dynamics. Faezeh [5] et al presented a model-based gait recognition using arm and leg movement.

The initial body model and the posterior model were constructed on anatomical proportions and the articulated parts of the body by active contour models and the Hough transform. A skeleton model, which divided the body into head, neck, torso, left and right thighs, and left and right shins, was created by Jure Kovac [6] et al. While model-based methods have advantages, such as strong anti-interference, low feature dimension and accurate description for the change of each part of body, there are great difficulties in the process of modeling tracking and matching [7]. Silhouette-based algorithm gains the body permanents (speed, shape, texture and color) from the gait image sequence directly without creating any special model of human body or motion and analyses the relationship of those body permanents between different gait patterns in one sequence to achieve the gait recognition. Zeng [8] et al presented a new silhouette-based gait recognition method which combines physical parameters and spatio-temporal motion characteristics of human subject. H-W ratio (the ratio of the silhouette's height and width) was fused with the width of the outer contour of the silhouette, the silhouette area and the vertical coordinate of

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centroid of the outer contour to accomplish the recognition. Lee [9] et al introduced a gait recognition algorithm based on TAMHI(time-sliced averaged motion history image) and HOG (histograms of oriented gradients), which preserves more detailed instantaneous information of gait cycles and reflects the walking speed well. Ju [10] et al proposed GEI (gait energy image) to characterize human walking properties. GEI was composed of static body silhouette and dynamic motion of human gait for recognition and it was insensitive to noise.

However, human gait recognition also has difficulties, such as low quality silhouette with complicated background, complex calculation in recognition and the problem of practicability. Curvelet presented by famous academics Candes and Donoho [11] is based on the principle that curve can be approximated by straight line in local regions and it translates the singularity of curve into linear singularity in image or signal. The basis functions of Curvelet transform can be any direction and various shapes. Thus, according to its size, the image or signal can be described by different angles and different directions. The pattern information can be expressed accurately and sparsely by the nonzero coefficients of Curvelet transform which concentrate the image energy and help to analyze the important texture feature and edge feature of image. At present, Curvelet transform has been applied to image processing [12-15].

Combined with the accurate description of the edge and texture information by Curvelet transform, a gait recognition method using GEI and Curvelet (GEIC) is presented. The energy coefficients of Curvelet transform are selected to express the static body silhouette and motion frequency, which can not only use the information of GEI adequately but also reduce the feature dimension. Thus, the proposed algorithm can improve the efficiency of recognition and basically satisfy the real-time requirement.

2 Gait recognition

Gait recognition is the process of analyzing and identifying the human motion sequence, which includes image preprocessing, gait cycle detection, feature extraction and classification. The flow chart of the algorithm GEIC proposed is shown in Fig. 1.

2.1 Preprocessing

Since the locations of the body in one sequence are different, those images should be normalized and centralized before extracting GEI to reduce redundant information computation complexity. The width and height of the body are two important cues in gait recognition. By observing, the width of the silhouette is changing periodically with the timelapse. It reaches its maximum when the two legs are farthest apart (full stride stance) and drop to its minimum when the legs overlap (heels together stance). At the same time, the height of the silhouette changes slightly in the procedure. Consequently, we can get the estimation of the gait cycle

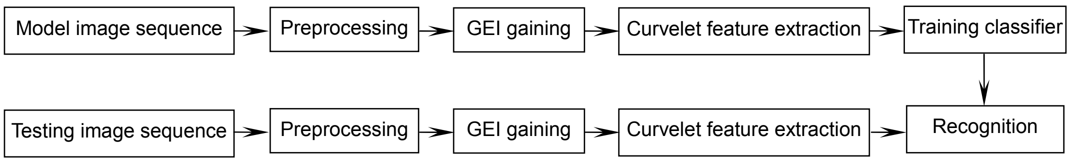

Fig. 1 GEIC algorithm flow chart.

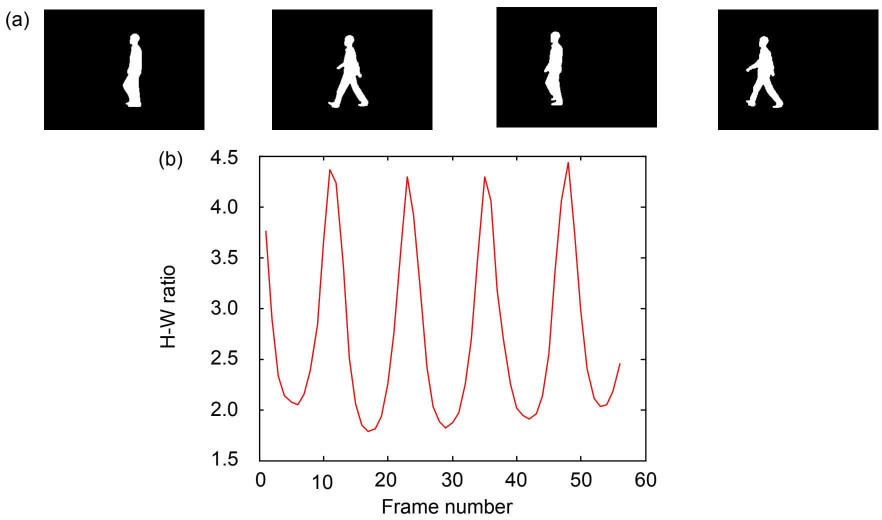

Fig. 2 (a) Four cases of reaching extreme point in one gait cycle. (b) The H-W ratio curve of a gait sequence.

2017, Vol 44, Issue 4

through analyzing the aspect ratio of a gait sequence (height/width, H-W ratio). For each frame in one sequence, the maximal and minimum widths of the silhouettes and the variances of H-W ratio are shown in Fig. 2.

Obviously, the aspect ratio displays periodic variation. Because of the symmetry between the case that their right foot behind their left foot and the contrary case, the sequence between three adjacent maxium values is selected as a gait cycle.

In order to avoid the loss of the height difference among individuals, the vertical point is selected to unify the body in the box with a size of 181×128. The original gait image and the corresponding image after normalized are shown in Fig. 3.

2.2 GEI extraction

GEI reflecting gait characteristic is gained from a cycle gait image by using weighted average method. Suppose that $I(x,y)$ represents the preprocessed gait image, GEI can be computed by formula (1):

$$G(x,y)=\frac{1}{N}\sum_{i=1}^{N}I_i(x,y)\,, \tag{1}$$

where (x, y) is the pixel coordinate of image, N represents the sequence number of a gait cycle and i represents the number of the frames used for calculation. A cycle of gait sequence images and the extracted GEI are shown in Fig. 4, GEI contains both the static silhouette feature and the dynamic frequency of each part of human body in the process of walking. The lighter pixels in GEI reflect the static information in walking while the parts darken gradually describe the motion information.

2.3 Curvelet feature extraction

In essence, Curvelet transformation is a multi-scale pyramid decomposition, which reflects one image at different directions and scales. However, this pyramid is nonstandard because the length and width which are the square of length in each Curvelet are variable. On account of the accurate description of the detail and direction information of gait frequency by Curvelet transform, the Curvelet features based on GEI are selected as gait characteristics.

Before extracting Curvelet feature, the Curvelet coefficients should be acquired. Curvelet coefficients are acquired from GEI by the second generation Curvelet transform using FDCT_WARP (Wrapping of specially selected Fourier samples). The process is as follow:

1) The Fourier frequency function $\hat{F}[n_1,n_2]$ is gained by two dimension fast Fourier transform (2DFFT). Where $-(n/2)\le(n_1,n_2)\le(n/2)$ and n is the smaller size of image.

2) The new sampled function $\hat{F}[n_1,n_2,-n_1\tan\theta_l]$ ($(n_1,n_2)\in P_j$) is sampled from $\hat{F}[n_1,n_2]$ on every angle and scale (j, l).

$$\tan\theta_l = l\times 2^{\lfloor -j/2\rfloor}, l=-2^{\lfloor -j/2\rfloor},\dots,2^{\lfloor -j/2\rfloor}-1\,, \tag{2}$$

$$P_j=\{(n_1,n_2): n_{1,0}\le n_1< n_{1,0}+l_{1,j},\ n_{2,0}\le n_2< n_{2,0}+l_{2,j}\}\,, \tag{3}$$

where $(n_{1,0}, n_{2,0})$ is the coordinate of the point at the far left of the rectangular box, and $l_{1,j}\approx 2^j, l_{2,j}\approx 2^{j/2}$.

3) The Fourier frequency window $U_j(n_1,n_2)$ is

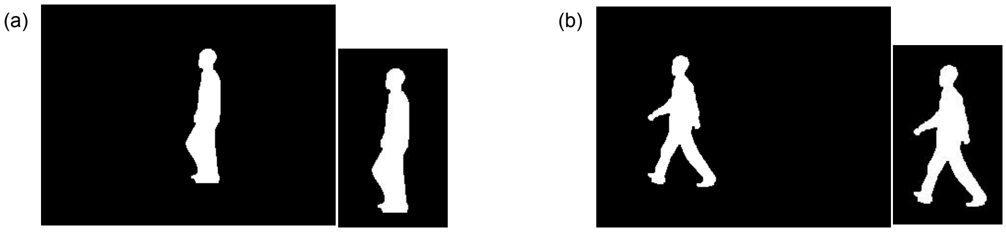

Fig. 3 Gait silhouette normalizing.

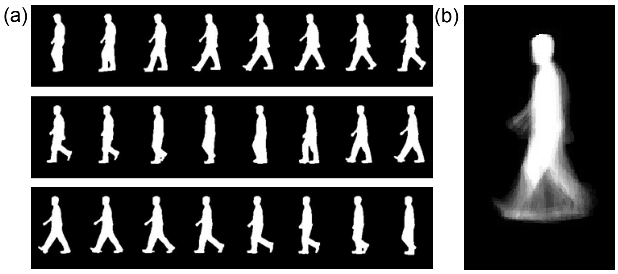

Fig. 4 (a) A cycle of Gait sequence images. (b) The corresponding GEI.

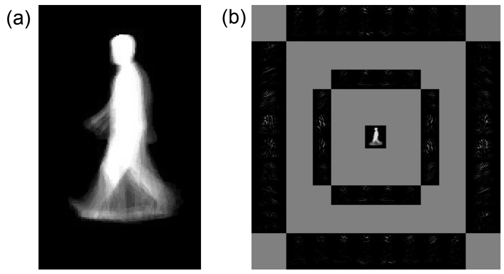

Fig. 5 (a) GEI. (b) The responding Curvelet decomposition.

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multiplied by $\hat{F}[n_1, n_2, -n_1 \tan\theta_l]$:

$$\widetilde{F}_{j,l}(n_1,n_2) = \hat{F}[n_1, n_2, -n_1 \tan\theta_l] \times U_j(n_1,n_2) . \quad (4)$$

4) The Curvelet coefficients $C_{j,l}$ can be obtained by two dimension inverse fast Fourier transforming(2DIFFT) to every $\widetilde{F}_{j,l}(n_1,n_2)$.

The responding images using Cartesian coordinate system coaxial aperture are shown in Fig. 5.

As shown in Fig. 5, the texture information of GEI is reflected in the lighter, which are also the important Curvelet coefficients. The low frequent information, $C_{1,1}$, is located at the center of the figure, while Curvelet coefficients of scales 2 and 3 which reflect the high frequent information are from the inside out. Scale 2, like with scale 3, includes 4 strips which correspond to the Curvelet coefficients of the four quadrants, respectively. Each sub-segmented block reflects to the corresponding scale and direction.

In the process of Curvelet decomposition, there is 1 direction at the first scale and 16 directions at the second scale, while the third scale has 32 directions and the fourth scale has 1 direction. Because the primary functions for decomposition are different and the direction information of image is expressed well by Curvelet coefficients at different scales and different directions, the detail information and direction can be approximated by the Curvelet coefficients of each sub-black in a large degree. Thus, average l_1 norm is selected to extract every scale Curvelet coefficients feature and it is computed by formula (5):

$$E_k = \frac{1}{MN} \sum_{i}^{M} \sum_{j}^{N} \left| x_k(i,j) \right| , \quad (5)$$

where $|x_k(i, j)|$ is the length of x_k. While the number of all directions in Curvelet decomposition is 50, the feature vector is denoted as $f=[E_1, E_2, E_3, \ldots, E_{49}, E_{50}]$, which reflects not only the massive human structure of GEI but also the detail information of gait frequency. The Curvelet energy coefficients at all directions in GEI are shown in Table 1.

3 Experimental results and analyses

CASIA (B) database built by Institute of Automation, Chinese Academy of Sciences is selected to demonstrate the proposed algorithm GEIC and it is composed by the gait sequences of 124 people. Everyone has 11 visual angles (0°,18°,…,180°) and three species of gait including 6 normal gait, 2 wearing gait and 2 packaging gait.

3.1 Training sets and testing sets selection

This paper chooses the data set at the view of 90° sets to accomplish identity recognition, which was divided into 3. Set 1 is normal gait, while set 2 is wearing gait and set 3 is packaging gait. The selection of training sets and testing sets are shown in Table 2.

Table 1 The Curvelet feature of GEI.

Feature	1	2	3	4	5	6	7	8	9	10
Value	12247.9	140.705	326.293	349.155	216.235	251.192	446.521	617.081	345.962	140.705
Feature	11	12	13	14	15	16	17	18	19	20
Value	326.293	349.155	216.235	251.192	446.521	617.081	345.962	56.89389	100.066	111.513
Feature	21	22	23	24	25	26	27	28	29	30
Value	151.409	138.979	131.168	60.783	49.7588	61.3174	80.2487	91.9216	135.123	223.940
Feature	31	32	33	34	35	36	37	38	39	40
Value	178.354	70.7249	77.8300	56.8939	100.066	111.513	151.409	138.979	131.168	60.7834
Feature	41	42	43	44	45	46	47	48	49	50
Value	49.7588	61.3174	91.9216	91.9216	135.123	223.940	178.354	70.7249	77.8300	210.850

Table 2 Training and testing selection of Sets1, Sets2 and Sets3.

	Number of people	Sequence number of one person			Total		
		Set 1	Set 2	Set 3	Set 1	Set 2	Set 3
Training	124	1	1	1	124	124	124
Testing	124	5	1	1	620	124	124

Table 3 The recognition rate of different algorithms.

	CEI+KPCA	GEI+(2D)2PCA	GEI+W(2D)2PCA	GEIC
Normal gait/%	75.5	79.4	80.2	85.5
Packaging gait/%	79.0	81.5	83.0	87.1
Wearing gait/%	78.2	84.6	86.2	87.9
Average/%	77.57	81.83	83.13	86.83

3.2 Experimental results and analyses

GEIC proposed is compared with GEI+KPCA [16], GEI+(2D)2PCA and GEI+W(2D)2PCA [17]. The recognition experiments are shown in Table 3.

From Table 3, the presented algorithm GEIC is superior to GEI+KPCA, GEI+(2D)2PCA and GEI+ W(2D)2PCA with the recognition rate of 85.5% on normal gait, the rate of 87.9% on wearing gait and the rate of 87.1% on packaging. The experimental results show that the effectiveness of GEIC is better than GEI+KPCA, GEI+(2D)2PCA and GEI+W(2D)2PCA on the condition of the person wearing clothes or packaging. Thus, the proposed algorithm based on GEI and Curvelet for gait recognition (GEIC) has achieved high performance.

4 Conclusions

GEI is composed of static body silhouette and motion frequency of human gait for recognition and it can overcome the influence of image quality. Combined with the accurate description of the edge and texture of image by Curvelet transform, a new gait recognition method using GEI and Curvelet is presented. The information of human body silhouette and motion frequency in GEI can be expressed accurately by Curvelet with lower energy coefficients in the multi-scale which consider the view of the edge and texture. Using the energy coefficients of Curvelet transform as gait feature vector can not only improve the recognition efficiency, but also reduce the dimension of gait feature which basically satisfies the real-time requirement.

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