The gait and face image processing

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Abstract. Dealt with the deficiency of single creature feature classification, classification methods of gait and facial side integrating at the feature layers are brought forth to improve the identify classification rate with long distance. This paper respectively has feature extraction and dimension reduction process for analyzing gait energy diagram and side facial image by multivariate discriminant analysis for Matrix component analysis of dichroic image to get original feature matrix to make vectorication, fusing feature eigenvector, and then feature fusion for fusing feature eigenvector by multiple discriminant analysis techniques to obtain the fusing eiqenvector of gait and facial image, at final nearest neighbour methods identifies identity. Testing for the above-mentioned data by CASIA Dataset B gait database. The results show that it improves the accurate classification rate to test the effectiveness of this method providing a new way for multi-biometric features classification.

Introduction

Kale, etc. uses mono vidicon to make fusing classification for invariant optic angle gait and facial classification decision layer. Shakhnarovich, etc uses visible shell generation method for four vidicons to shoot a serious of mono visual diagram for rebuilding 3D model to follow and recognize the visible regulated object. Zhou, etc designs a classification system by using single vidicon to get side human body video to extract the gait outline and side face to identify the fusing of gait and facial image. Zhou and Bhanu, etc uses mono vidicon to identify the long distance gait and side facial image on matching layer and feature layer. Li Yi, etc makes classification based on Fourier transform and singular score decomposition methods. Liu Huanxi uses classification by single mode creature feature of sustance learning algorithms.

Preprocessing for Gait and Facial Image

For gait diagram sequence, make background modeling to get background image. Foreground aimed human image obtained by background subtraction uses connected analysis to eliminate small area to get rather complete aimed human image. Binaryzation for aimed human image operates by mathematical morphological methods to fill in the cavity and get rid of noise fringed on gait image to test the outline sequence with cycle detection to compound gait energy diagram. In addition, in preprocessing for gait and facial image, the complete foreground aimed human image extracts head section and graying to test side face. A periodical sequence two score gait outline image generates GEI like shown as Figure 1. The head image position of face is like shown as Figure 2.

Fig.1. GEI

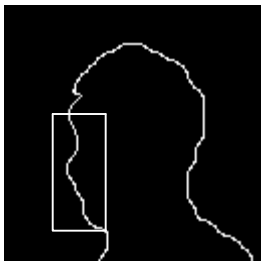


Fig.2. Schematic diagram side facial detection

Fusing Classification for Gait and Face Image.

Video image sequence gets gait energy diagram and side human diagram by gait and human image preprocessing to fuse and identify the gait energy image and side facial image on feature layer. Combining 2DIMPCA and multiple discriminant analysis brings a kind of classification of gait and facial feature fusing.

Feature extraction

There are $r_g \times s_g$ testing sample gait energy diagram of n_g like $\mathbf{X}_1, \mathbf{X}_2, \Lambda, \mathbf{X}_{n_g}$ and $r_f \times s_f$ testing sample side face image of n_f like $\mathbf{A}_1, \mathbf{A}_2, \Lambda, \mathbf{A}_{n_f}$ .The IMPCA operation respectively are for testing sample gait energy diagram and side facial image on the horizontal direction to find the best projection matrix $\mathbf{U}_g$ and $\mathbf{U}_f$.

The population variance matrix of gait energy diagram and side facial diagram are respectively:

$$\mathbf{G}_t^g = \frac{1}{n_g}\sum_{i=1}^{n_g}(\mathbf{X}_i - \overline{\mathbf{X}})^{\mathrm{T}}(\mathbf{X}_i - \overline{\mathbf{X}}), \tag{1}$$

$$\mathbf{G}_t^f = \frac{1}{n_f}\sum_{i=1}^{n_f}(\mathbf{A}_i - \overline{\mathbf{A}})^{\mathrm{T}}(\mathbf{A}_i - \overline{\mathbf{A}}), \tag{2}$$

In which, $\overline{\mathbf{X}} = \sum_{i=1}^{n_g}\mathbf{X}_i$, $\overline{\mathrm{A}} = \sum_{i=1}^{n_f}\mathbf{A}_i$. The dominant eigenscore for the first k_g of $\mathbf{G}_t^g$ corresponds with the eigenvector as the best projection matrix $\mathbf{U}_g = [\mathbf{u}_1^g, \mathbf{u}_2^g, \Lambda, \mathbf{u}_{k_g}^g]$. The dominant eigenscore for the first k_f of $\mathbf{G}_t^f$ corresponds with the eigenvector as the best projection matrix $\mathbf{U}_f = [\mathbf{u}_1^f, \mathbf{u}_1^f, \Lambda, \mathbf{u}_{k_f}^f]$. Through IMPCA dimensionality reduction as horizontal direction of gait energy diagram and side facial image, the feature matrix of $r_g \times k_g$ and $r_f \times k_f$ is like:

$$\mathbf{Y}_i = \mathbf{X}_i\mathbf{U}_g (i = 1,2,\Lambda, n_g), \tag{3}$$

$$\mathbf{B}_i = \mathbf{A}_i\mathbf{U}_f (i = 1,2,\Lambda, n_f) 。 \tag{4}$$

IMPCA operation for $\mathbf{Y}_i (i = 1,2,\Lambda, n_g)$ and $\mathbf{B}_i (i = 1,2,\Lambda, n_f)$ on the vertical direction by diagram matrix transpose instead of IMPCA operation, that is IMPCA for $\mathbf{Y}_i^{\mathrm{T}} (i = 1,2,\Lambda, n_g)$ and $\mathbf{B}_i^{\mathrm{T}} (i = 1,2,\Lambda, n_f)$ to find the best projection matrix $\mathbf{V}_g$ and $\mathbf{V}_f$. According to the total variance matrix formula, the scores of $\mathbf{Y}_i^{\mathrm{T}} (i = 1,2,\Lambda, n_g)$ and $\mathbf{B}_i^{\mathrm{T}} (i = 1,2,\Lambda, n_f)$ are like:

$$\mathbf{H}_t^g = \frac{1}{n_g}\sum_{i=1}^{n_g}(\mathbf{Y}_i^{\mathrm{T}} - \overline{\mathbf{Y}^{\mathrm{T}}})^{\mathrm{T}}(\mathbf{Y}_i^{\mathrm{T}} - \overline{\mathbf{Y}^{\mathrm{T}}}), \tag{5}$$

$$\mathbf{H}_t^f = \frac{1}{n_f}\sum_{i=1}^{n_f}(\mathbf{B}_i^{\mathrm{T}} - \overline{\mathbf{B}^{\mathrm{T}}})^{\mathrm{T}}(\mathbf{B}_i^{\mathrm{T}} - \overline{\mathbf{B}^{\mathrm{T}}}) 。 \tag{6}$$

In which, $\overline{\mathbf{Y}^{\mathrm{T}}} = (1/n_g)\sum_{i=1}^{n_g}\mathbf{Y}_i^{\mathrm{T}}$, $\overline{\mathbf{B}^{\mathrm{T}}} = (1/n_f)\sum_{i=1}^{n_f}\mathbf{B}_i^{\mathrm{T}}$. The eigenvector of dominant eigenscore for the first l_g of $\mathbf{H}_t^g$ corresponds with the best projection matrix $\mathbf{V}_g = [\mathbf{v}_1^g, \mathbf{v}_2^g, \Lambda, \mathbf{v}_{k_g}^g]$, The eigenvector

of dominant eigenscore for the first l_f of $\mathbf{H}_t^f$ corresponds with the best projection matrix $\mathbf{V}_f = [\mathbf{v}_1^f, \mathbf{v}_2^f, \Lambda, \mathbf{v}_{k_f}^f]$. The original feature matrix of $k_g \times l_g$ and $k_f \times l_f$ is like:

$$\mathbf{Z}_i = \mathbf{Y}_i^{\mathrm{T}} \mathbf{V}_g = (\mathbf{X}_i \mathbf{U}_g)^{\mathrm{T}} \mathbf{V}_g (i = 1,2,\Lambda, n_g), \tag{7}$$

$$\mathbf{C}_i = \mathbf{B}_i^{\mathrm{T}} \mathbf{V}_f = (\mathbf{A}_i \mathbf{U}_f)^{\mathrm{T}} \mathbf{V}_f (i = 1,2,\Lambda, n_f)。 \tag{8}$$

Feature fusing

By 2DIMPCA feature extraction and dimensionality reduction, the original gait feature matrix $\mathbf{Z}_i (i = 1,2,\Lambda, n_g)$ of smaller dimension and original facial feature matrix $\mathbf{C}_i (i = 1,2,\Lambda, n_f)$ have larger differences with different dynamic range. Direct feature fusing causes larger data proportion disorder, for eliminating this kind of non-balance influence, the gait original matrix $\mathbf{Z}_i (i = 1,2,\Lambda, n_g)$ and facial original feature matrix $\mathbf{C}_i (i = 1,2,\Lambda, n_f)$ vectorizes with normalization data to make them at same range. This paper makes normalization of estimated score about mean score and variance. For testing sample I, the eigenvector dimension is L, each representation in components for eigenvector is shown as w_{ij}, normalization is like:

$$\hat{w}_{ij} = \frac{w_{ij} - \overline{w}_j}{\sigma_j} (i = 1,2,\Lambda, I, j = 1,2,\Lambda, L), \tag{9}$$

In which,component mean score is $\overline{w}_j = (1/I)\sum_{i=1}^{I} w_{ij}$ and component covariance is $\sigma_j^2 = (1/(I-1))\sum_{i=1}^{I} (w_{ij} - \overline{w}_j)^2$. Gait and facial original feature matrix have vectorizes with normalization to get vector quantity $\hat{\mathbf{Z}}_i (i = 1,2,\Lambda, n_g)$ and $\hat{\mathbf{C}}_i (i = 1,2,\Lambda, n_f)$.

Assumption that someone k has gait feature vector and facial feature vector after normalization are respectively $\hat{\mathbf{Z}}_i^k \in \mathrm{R}^{N_g} (i = 1,2,\Lambda, n_g^k)$, $\hat{\mathbf{C}}_j^k \in \mathrm{R}^{N_f} (j = 1,2,\Lambda, n_f^k)$. In which, N_g, N_f represent respectively gait and human facial feature vectorial dimension. n_g^k and n_f^k represents the amounts of gait of human k and facial feature vector, so the fusing feature victor for human k could be got as followed:

$$\mathbf{h}_l^k = [\hat{\mathbf{Z}}_i^k \quad \hat{\mathbf{C}}_j^k] (i = 1,2,\Lambda, n_g^k, j = 1,2,\Lambda, n_f^k), \tag{10}$$

In which, $l = i \times j$, $\mathbf{h}_l^k \in R^{N_g + N_f}$. The gait and human face are inter independent creature feature by using the human feature information, so the most amounts fusing feature victor $\mathbf{h}$ are appeared by possibility gait feature and human facial feature.

Feature fusing

Gait and human facial fusing feature victor $\mathbf{h}$ obtained use the multi discriminant analysis techniques to pull categories distance and shorten categories distance for improving the classification parameter and fusing fusing eigenvector $\mathbf{h}$. MDA finds transformational matrix $\mathbf{W}$ to make specific scores large of sample categories dispersion matrix $\mathbf{S}_B$ and categories dispersion matrix $\mathbf{S}_W$ to improve category strength. Introducing criterion function:

$$J(\mathbf{W}) = \frac{\left|\mathbf{W}^{\mathrm{T}} \mathbf{S}_B \mathbf{W}\right|}{\left|\mathbf{W}^{\mathrm{T}} \mathbf{S}_W \mathbf{W}\right|}, \tag{11}$$

In which, $\mathbf{S}_W = \sum_{i=1}^{c} \sum_{\mathbf{h} \in V_i} (\mathbf{h} - \mathbf{m}_i)(\mathbf{h} - \mathbf{m}_i)^{\mathrm{T}}$, $\mathbf{S}_B = \sum_{i=1}^{c} n_i (\mathbf{m}_i - \mathbf{m})(\mathbf{m}_i - \mathbf{m})^{\mathrm{T}}$, V_i represents the i testing sample subset, V represents overall testing sample, c represents category number, n_i shows the number samples and n represents the overall testing sample numbers, $\mathbf{m}_i = (1/n_i)\sum_{\mathbf{h} \in V_i} \mathbf{h}$, $\mathbf{m} = (1/n)\sum_{\mathbf{h} \in V} \mathbf{h}$. When $J(\mathbf{W})$ got the maximum score, the vector quantity of optimal matrix $\mathbf{W}$ corresponds the eigenvector of the maximum eigenvector scores in formal (12).

$$\mathbf{S}_B \boldsymbol{\omega}_i = \lambda_i \mathbf{S}_W \boldsymbol{\omega}_i, \tag{12}$$

The non zero eigenscore in formal (12) has $c-1$ at most corresponding the eigenvector $\boldsymbol{\omega}_i$ formed into matrix $\mathbf{M}_{mda}$, so gait and human facial fusing eigenvector by multiple discriminant analysis techniques:

$$\mathbf{z}_k = \mathbf{M}_{mda}^{\mathrm{T}}\mathbf{h}_k (k = 1,\Lambda\ ,n)\text{。} \tag{13}$$

In which $\mathbf{M}_{mda} = [\boldsymbol{\omega}_1, \boldsymbol{\omega}_2, \Lambda\ , \boldsymbol{\omega}_r](r \le c-1)$.

Classification process

Finally, the identity classification is on by nearest neighbour methods, the Euclidean distance as similitude measurement. Assuming there are N_i samples, $i = 1,2,\Lambda\ ,c$. The discrimination function is like:

$$g_i(\mathbf{x}) = \min\left\|\mathbf{x} - \mathbf{x}_i^k\right\|(k = 1,2,\Lambda\ ,N_i)\ , \tag{14}$$

In which $\mathbf{x}$ represents the unknown sample, $\mathbf{x}_i^k$ represents the k samples of sample library.

If $g_j(\mathbf{x}) = \min_i g_i(\mathbf{x})(i = 1,2,\Lambda\ ,c)$, the corresponding people pf category i is classification result

Experimental Results and Analysis

This paper uses 123 people of CASIA Dataset B, three experiments under the normal condition of visual angle 90° make a testing sample by the 1,3,5 sequences and the corresponding 2,4,6 sequences as testing samples. Gait energy diagram size is 128X88, the side facial diagram size is 16X10. Under the circumstance of dimensionalisy reduction without influences for classification rate, for gait, the horizontal direction is $\alpha = 90\%$, vertical direction is $\alpha = 99\%$, for facial image, horizontal direction is $\alpha = 99\%$, vertical direction is $\alpha = 99\%$. Figure I lists the three units the extracted original feature matrix dimension of gait energy diagram and side facial image by 2DIMPCA. It is shown that 2DIMPCA could decrease largely the gait and side facial features.

Figure1.2 Extracted feature dimension by 2DIMPCA

Tab.1.

	Unit one	Unit two	Unit three
Gait image	27×9	28×10	28×10
Facial image	8×6	9×6	9×6

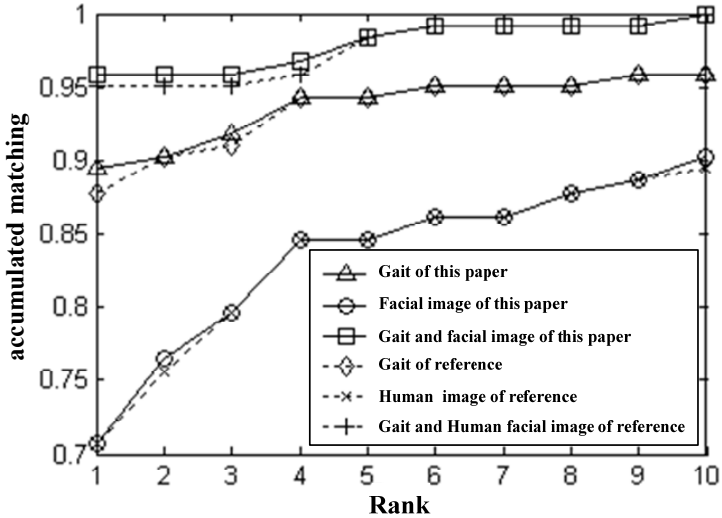
(1) CCR(Correct Classification Rate): Figure II lists experimental correct classification rate and average correct classification rate for three units.

CCR(%)Figure 2 correct classification rate CCR(%)

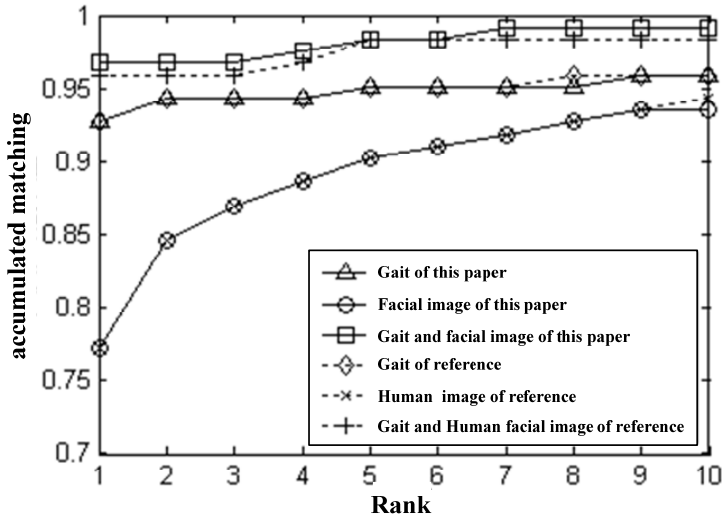
Tab.2.

	Methods of this paper			Reference methods		
	Gait	Facial image	Fusion of gait and facial image	Gait	Facial image	Fusing of gait and facial image
Unit one	89.4	70.7	95.9	87.8	70.7	95.1
Unit two	92.7	77.2	96.7	92.7	77.2	95.9
Unit three	89.4	72.4	95.1	91.1	71.5	94.3
Average score	90.5	73.4	95.9	90.5	73.1	95.1

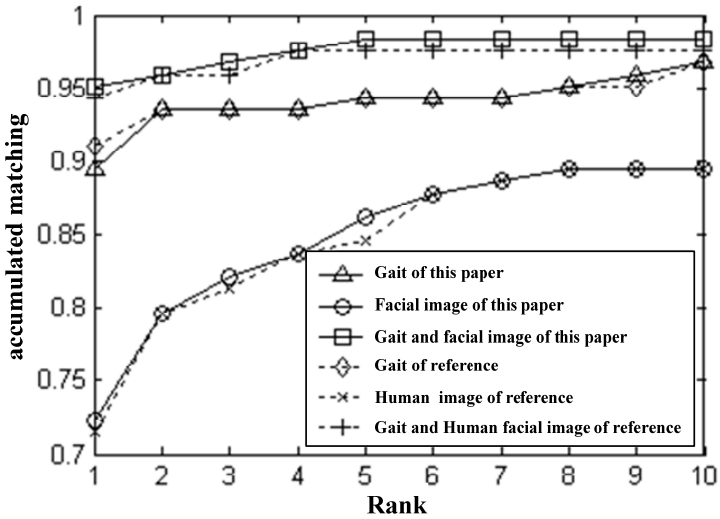
(2) Cumulative Match Score: CMS describes not the correct matching results for the maximum matching score but whether the correct matching results lies in the the former testing sample with larger matching score or not. CMS is statistics classification results to display the searched testing sample numbers called as Rank under the correct classification rate circumstance, the horizontal axis shows Rank, the vertical axis shows accumulated matching score (the classification score of the current rank) to draw the corresponding CMS curve of machine results. Figure 3 shows the experimental accumulated matching score for each unit.



(a) CMS curve of unit one



(b) CMS curve of unit two



(c) CMS curve of unit three

Fig.3. Experimental CMS curve of all units

(3) Classification Time: classification time shows the efficiency of classification methods. Classification time is an important indicator of classification time system. Figure III shows the overall classification time for 123 people of three units.

Figure 3 Classification time (s)

Tab.3.

	Methods of this paper			Reference methods		
	Gait	Facial image	Fusing gait and facial image	Gait	Facial image	Fusing gait and facial image
Unit one	19.811	3.916	54.439	21.698	5.292	111.700
Unit two	19.726	3.886	53.312	21.566	5.195	114.216
Unit three	19.863	3.942	56.502	21.742	5.302	108.112
Average score	19.800	3.908	54.751	21.669	5.263	111.343

Comprehensive analysis for the experimental algorithm results of this paper:

(1) From the correct classification rate, fusing gait and human facial feature of 2DIMPCA and MDA are effect than single creature feature, the classification rate has obvious wide improvement, at the same time, the comparison of methods of this paper and reference[8] finds the same classification rate, but the higher classification rate for this paper is about gait and facial fusing classification.

(2) From classification time, this paper has advantages than reference[8] to explain the efficiency of this paper is more higher for application in the real-time system.

Conclusion

ures classification as a hot point for current biometric features classification technique and the trend of future identify classification system, the fusing classification method is brought about gait and facial image on feature layer to test and evaluate by using the CASIA Dataset B gait database of Chinese Academy of Sciences and to design the classification prototype system of gait and human facial image. Seen by the experimental results, this paper obtains the satisfied correct classification rate.

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