

Face Expression Recognition Using False Geodesic Distance

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Abstract. Expression recognition is a branch of face recognition. This paper describes how a 3D model rebuilds from 2D static face image through specific algorithm and how the principle component better representing face characteristics is obtained by collecting geometrical characteristic information manifesting emotional variations through false geodesic distance in 3D space and eliminating the relativity of the characteristics extracted through Principal Component Analysis. At last the emotional mode of the samples to be tested shall be identified through distance test method by computing the Mahalanobis Distance between the test sample to be tested and the training sample.

Keywords: emotion face recognition; false geodesic distance; Principal Component Analysis Introduction

1 Introduction

In recent years, the facial expression analysis has attracted attentions from many computer vision researchers. In a broad sense, the facial emotion recognition based on static images includes: pretreatment, face detection, extraction of emotional characteristics and emotions classification [1] [2]. This paper represents an expression recognition method by manifesting the facial characteristics through false geodesic distance and remodeling the facial expressions in the 3D space and verifies this method being able to identify different expressions from static facial images in a more effective and remarkable manner [3]. The experiments demonstrate that this method achieves better results of expression recognition than traditional methods and shows stronger robustness to changes of illumination.

2 Computation Based on False Geodesic Distance

First, select 6 facial images from the Yale faces collection, each containing 5 emotions: normal expression, happiness, surprise, frown and sadness.

Suppose the entire facial plane is referred to as E, nose, cheekbone and forehead are respectively referred to as A^0 , B^0 and C^0 , and function F is the function for heights

of arbitrary points x and y within the plane, develop 3D facial model per the following 4 restrictions.

1. $\{F(x_A, y_A) < F(x_0, y_0) | \forall (x_A, y_B) \in A^o, (x_0, y_0) \notin A\} \cap \{F(x_A, y_A) < \alpha | \exists \alpha > 0, \forall (x_A, y_B) \in A^o\}$. 2. $\{F(x_B, y_B) < F(x_A, y_A) | \forall (x_A, y_A) \in A^o, (x_B, y_B) \in B^o\} \cap \{|F(x_B, y_B) - F(x_C, y_C)| < \beta | \exists \beta > 0, \forall (x_B, y_B) \in B^o, (x_C, y_C) \in C^o\} \cap \{F(x_B, y_B) > F(x, y) | \forall (x_B, y_B) \in B^o, (x, y) \in Cu_E(A \cup B \cup C)\}$. 3. Establish (x^*, y^*) as the centre point of section E, where $X = (x^*, y^*), Y = (x_1, y_1), Z = (x_2, y_2)$ then $\{F(x_1, y_1) > F(x_2, y_2) | \|X - Y\| > \|X - Z\|, X, Y, Z \in E\}$ and $\{F'(x_A, y_A) > F'(x_B, y_B) > F'(x_C, y_C) | (x_A, y_A) \in A^o, (x_B, y_B) \in B^o, (x_C, y_C) \in C^o\}$. 4. Establish $\{(x, y) | \min F(x, y) = \gamma, (x, y) \in Cu_E(A \cup B \cup C)\}$. As the set of points representing the minimum value of the function, so it comes to $\{|F(x, y) - \gamma| < \varepsilon | \exists \varepsilon > 0, \forall (x, y) \in Cu_E(A \cup B \cup C)\}$.

Identify A, B and C zones based on the decomposition results, reduce the impact of illuminations and establish 3D model per restrictions [4] [5]. Extract from the developed 3D image the following attribute value [6] through false geodesic distance: length of face, width of face, brow width, brow height, vertical distance between centre of brow and that of eyes, eye width, distance between upper and lower eyelids, mouth width and the distance between upper and lower lips.

3 Emotion Recognition Based on PCA and False Geodesic Distance

Suppose there are n samples of facial models, each with p attributes observed, the following initial data information matrix is achieved. Then take p vectors of the data matrix as aggregate indicator vectors:

$$F_1 = \alpha_{11}X_1 + \alpha_{12}X_2 + \dots + \alpha_{1p}X_p \dots \dots F_p = \alpha_{p1}X_1 + \alpha_{p2}X_2 + \dots + \alpha_{pp}X_p$$

Recorded as: $F_i = \alpha_{i1}X_1 + \alpha_{i2}X_2 + \dots + \alpha_{ip}X_p$ which $\alpha_{i1}^2 + \dots + \alpha_{ip}^2 = 1$ where $i = 1, 2, \dots, p$. Coefficient α_{ij} is determined by the following principle:

1. F_i and F_j are uncorrelated $i \neq j; i, j = 1, 2, \dots, p$.

2. F_1 holds the biggest variance among all linear combination. Similarly, F_p is the p^{th} biggest variance among all linear combinations of X_1, X_2, \dots, X_p which are entirely uncorrelated with F_1, F_2, \dots, F_{p-1} . Set X as the Characteristic value of covariance matrix:

$$\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_p \text{ hence } \text{var } F_1 \geq \text{var } F_2 \geq \dots \geq \text{var } F_p > 0.$$

Supposing the contribution rate of the k^{th} principle component is $\lambda_k / (\lambda_1 + \dots + \lambda_j + \dots + \lambda_p)$ and the accumulated contribution rate of the first k principle components. See fig. 1. If the accumulated contribution rate exceeds 85%, this proves that the information obtained from the first k principle components has basically covered the information contained in all measurement indicators that reduce the number of variables and eliminate the dependencies between variables.

G_1 and G_2 , representing two totals, are the random variables obtained from R^n . Their mathematic expectation and variance are: $EG_1 = \mu^{(1)}, EG_2 = \mu^{(2)}$ $\text{var } G_1 = S^{(1)}, \text{var } G_2 = S^{(2)}$.

Suppose there is sample $x \in R^p$, the principle to judge if X is involved in G_1 or G_2 . If X is closer to G_1 , then X is involved in G_1 ; if X is closer to G_2 , X is involved in G_2 .

If Mahalanobis Distance $d(X, G_i)$ is employed, then:

$$d^2(X, G_i) = (X - \mu^{(i)})^T S^{-1} (X - \mu^{(i)}) \quad i = 1, 2$$

The square difference of distances between X and G_1 and X and G_2 is:

$$d^2(X, G_1) - d^2(X, G_2) = (X - \mu^{(1)})^T S^{-1} (X - \mu^{(1)}) - (X - \mu^{(2)})^T S^{-1} (X - \mu^{(2)}) = -2(X - \mu)^T S^{-1} (\mu^{(1)} - \mu^{(2)})$$

In which $\mu = (\mu^{(1)} + \mu^{(2)})/2$. Defined function: $U(X) = -2(X - \mu)^T S^{-1} (\mu^{(1)} - \mu^{(2)})$

If $d(X, G_1) \leq d(X, G_2)$, then $X \in G_1$; if $d(X, G_2) \leq d(X, G_1)$ $X \in G_2$
i.e. $U(X) \geq 0$ then $X \in G_1$; If $U(X) \leq 0$ then $X \in G_2$.

4 Experiment Result and Analysis

Select from Yale faces collections facial images as test samples, manifest the characteristics of the samples based on the 2D plane distance and the false geodesic distance, carry out principle component computation, compare against training samples and figure out the Mahalanobis Distance between the two types of samples and finally identify what categories the two to-be-tested samples belong to.

Data of F_1, F_2, F_3 represents results based on false geodesic distance and 2D plane distance. Table 4 shows results of emotion recognition by PCA method based on false geodesic distance and 2D plane distance.

Table 1. Results based on False Geodesic Distance and 2D Plane Distance

	F1	F2	F3	Actual Category	Identification Category
Sample.1	4.02/3.14	37.89/40.37	14.81/18.92	3	3
Sample.2	7.10/7.24	34.68/32.68	17.16/17.11	1	1
Sample.3	8.61/9.16	37.56/40.15	22.93/19.58	5	5
Sample.4	7.56/8.65	33.63/34.29	17.64/17.16	4	4
Sample.5	8.55/7.56	36.30/33.29	17.94/17.44	2	2

Map the three principle components of the training samples and “to-be-tested sample 1” from the two methods into 3D coordinates so as to read the results more intuitively. Fig. 2 shows the rate of recognition of different expressions from 30 static facial images based on the two methods. As we can see from NOR and SA expressions in the static facial images that they vary little in terms of geometric configurations, it is difficult for the traditional methods to discriminate this minor difference. However, the 3D-based method as described in this article may properly discriminate such difference and classify the expressions, displaying a more advantageous performance.

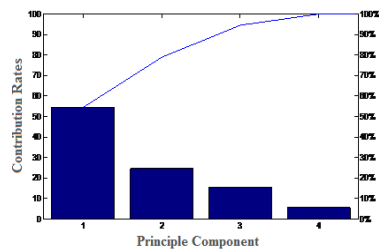


Fig. 1. PCC Rate

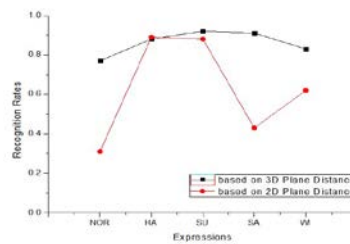


Fig. 2. Recognition Rate

5 Conclusion

This paper represents a PCA expression recognition method based on false geodesic distance. The test on the 30 facial samples selected from Yale faces collections demonstrates that this method is able to accurately recognize different expressions in static facial images and proves more effective and accurate than traditional methods, especially the accuracy in recognizing the emotions of static facial images with minor variations in geometric configurations.

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