Human Face Recognition Using Volume Feature, Fuzzy C-means and Membership Matching Score

SUPAWEE MAKDEE[1], CHOM KIMPAN [2], SERI PANSANG[3]

[1]Faculty of Industrial Technology, Rajabhat Ubon Ratchathani University, Ubonratchathani, THAILAND Email: mag_ubon@hotmail.com
[2]Faculty of Information Technology, Rangsit University, Bangkok, THAILAND Email: chom@rsu.ac.th
[3] Faculty of Science and Technology, Rajabhat Chiang Mai University, Chiang Mai, THAILAND Email: seri@academic.cmru.ac.th

Abstract: This study tends to propose the process of nose tip volume which is applied in face image recognition. Range image face database (RIFD) used in this face recognition is based on 3-D graphics database. For this advantage, we could solve scale, center and pose error problem by using geometric transform. Nose tip is assigned as the center to find volume feature. RIFD was transformed to the gradient face model for matching using the fuzzy membership adjusted by fuzzy c-means. The propose method was tested using facial range image from 130 people with normal facial expression. The output of the detection and recognition system has to be accurate for more than 80 percent and the processing time of the recognition system has to be better than [1-2] by the speeding up to 20 times.

Keywords: Face recognition, Volume Feature, fuzzy c-means and Membership Matching Score.

1 Introduction

Nowadays there are a lot public service organizations those need effective personal identification techniques for servicing a large number of people comfortably and fastly. Taking face recognition system for use in the organization is the best way. In the case of face recognition, there are two major problems to identify a person from an image of their face. Firstly, problems occur from environmental light noise, position of image size, and variation of pose. Those problems are difficult to control. Secondly, problem arise in face variation from person to person, such as facial expressions, action, aging, eye-glasses, posture, hairstyle, moustache and beard. The face recognition from RIFD is a very interesting topic due to its three dimensions range data characteristics. This type of data is more difficult to be altered or to be disguised, but it still can be helped solving the technical and the face variation problem better than 2-D image base. Currently, RIFD input machine has effectively created; therefore there is the potential for 3-D face recognition system by using the range image data.

Various related researches have indicated that most face recognition systems focus on a single pose [3-6]. Pose variation problems occur in single pose face recognition models when the pose position of the tested face was changed from the pose database value. Furthermore, single pose face recognition has not worked flexibly with variation of pose in the past and continues to be a problem.

This research proposes invariant range image multi-pose face recognition using volume clustering to recognize identity despite such variations in appearance that the face can have. The techniques use volume clustering to adjust ambiguity freely of various RIFD.

2 Data Acquisition

What is Range Image Face Data (RIFD)? It is a range data of faces in rectangular form, x and y are co-ordinate, and then $Z_{(x,y)}$ is ranged from base plane to face surface at x, y co-ordinate. The advantage of rectangular form is very easy for calculation.

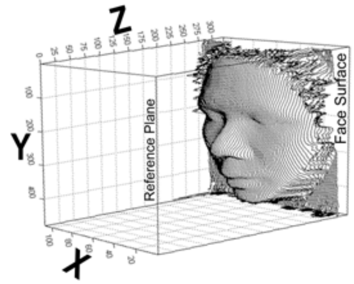

Fig.1 Range Image Face Data and a laser range finder

The human face is digitized into the range image data by using a laser range finder which is less sensitive to changes in environmental light [7-8]. Since the wavelength of a laser beam is different from the wavelength of ordinary visible light, it is easy to capture a laser image for calculating a range by means of simple triangular techniques.

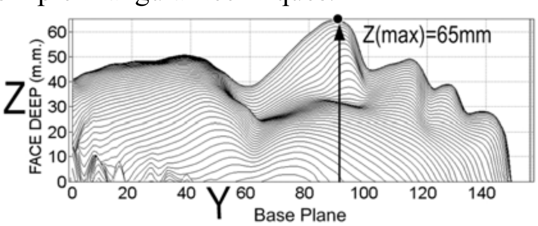

Fig.2 RIFD for use in the process

Digitized RIFD is used as a model to generate multi-pose RIFD by using geometric transform. Linear reduction is used for reduction of each pose image data size. Nose tip volume is used in extracting features from the data. The data is reduced again by ellipse face region extraction and finally the features are stored in a database.

3 Overview of the System

The overview of the face recognition system is illustrated in Figure3. There are two procedures in this system; *Registration* and *Recognitio*n. In the registration procedure, the faces of each tested subject that the system is required to acknowledge are added to the RIFD database. The human face is digitized into the range image data by using the laser range finder. The size is adjusted to 156 ×108 pixels with a range resolution of ± 1mm. The region of RIFD covers the area of about 240×166 sq.mm. This face size is the average for most Asian people.

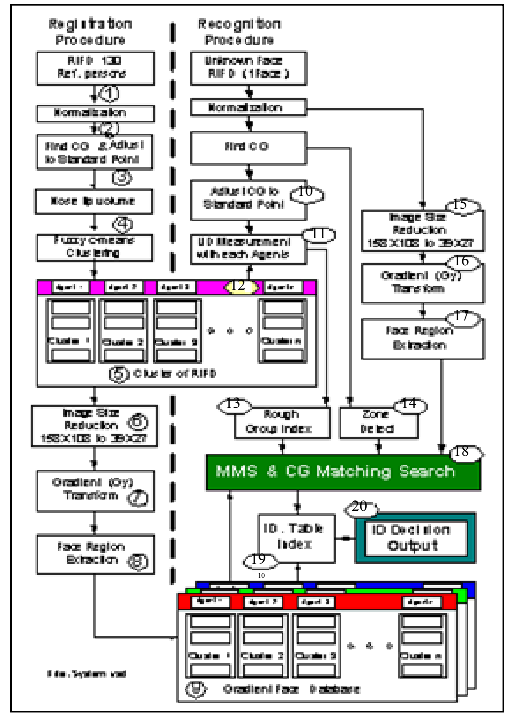

Fig.3 Overview of the face recognition system

Since acquisition process, scale and center are varied each time and difficult to be controlled which directly affects the recognition rate. It is necessary to normalization ① for adjusting the parameters of all RIFD to meet the standard values. After having carried out the normalization, RIFD will be searched for the center of gravity and the pose will be scrutinizingly fine-adjusted to the standard point ② for nose tip and calculate for nose volume③. Since FCM is collaborating with fuzzy relationship, which was created for searching the best similarity in the database. ④ In this case, the RIFD will be collected in database⑤ for which each cluster will have individual agent as a delegate. After that the data inside cluster of RIFD will be taken to reduce image size⑥, gradient transform⑦ for extracting face feature, extract only ellipse face area⑧ and sent to keep in Gradient Face Database⑨. In the recognition procedure, RIFD unknown face will be normalized similar to the registration procedure. After that the data will be divided into 2 parts. The first will be sent for evaluating the center of gravity and fine adjusted pose to standard point ⑩ in matching for data cluster searching and a delegate of cluster of RIFD ⑤. The second RIFD unknown face will be reduced by size, extracted face feature and region in block number 15,16, and 17, respectively. The evaluated CG of RIFD will be confined in Zone at block number 14. These data will be used as inputs of matching and searching process in block number 18.The result of this process will be used to open table for showing identification name of unknown face in block diagram number 20.

4 Registration Procedure

4.1 Normalization

Because the range image matrix is based on 3D graphics, the geometric transform [9] is used to normalize and solve the variation pose problem. By using Equation (1), the normalization and rotation of the pose position is combined.

$$V^* = T_0^{-1}(R(T_0(T_C(S \times V)))) \quad (1)$$

$$= (X^* Y^* Z^* 1)^T \quad (2)$$

$$V = (X \ Y \ Z \ 1)^T \quad (3)$$

$$S = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & S_y & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (4)$$

$$T_c = \begin{bmatrix} 1 & 0 & 0 & X_D \\ 0 & 1 & 0 & Y_D \\ 0 & 0 & 1 & Z_D \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (5)$$

$$T_0 = \begin{bmatrix} 1 & 0 & 0 & -X_C \\ 0 & 1 & 0 & -Y_C \\ 0 & 0 & 1 & -Z_C \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (6)$$

$$R_{(\alpha,\beta)} = \begin{bmatrix} \cos\beta & 0 & -\sin\beta & 0 \\ 0 & \cos\alpha & \sin\alpha & 0 \\ \sin\beta & -\sin\beta & \cos\beta & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (7)$$

where V^* is column vector of the new point, V is column vector of the original coordinate. S is the used matrix for scaling face size. $R_{(\alpha,\beta)}$ is rotational coordinate of points around X,Y axis by angle. α , β are rotated angles for up-down, left-right. T_0 is the matrix used for translating nose tip position to (0, 0, 0) Coordinate, T_c is the matrix used for translation of actual nose tip position to coordinate X_C, Y_C, Z_C (X_C, Y_C, Z_C) is reference point coordinate of the nose tip. (X_0, Y_0, Z_0) are original coordinate (0, 0, 0).

4.2 CG of RIFD

Since the RIFD is based on 3-D graphic data, the change of plane surface distance data will vary in accordance with the changed pose. Consequently, the center of gravity of RIFD can be used as an indicator of pose position of RIFD, approximately.

Root means square of $Z_{\max}$ is a appropriate threshold for distinguish interesting surface from face surface same RMS in electronic field. Then, the interesting area for searching CG can be described in equation 8.

$$InterestingArea = i_{\min} \text{ to } i_{\max}, j_{\min} \text{ to } j_{\max} \left| Z_{(i,j)} \geq \frac{Z_{\max}}{\sqrt{2}} \right. \quad (8)$$

The position of interesting area start from $i_{\min}$ to $i_{\max}$ and $j_{\min}$ to $j_{\max}$, when i and j are coordinate of Z only for $Z_{(i,j)} \geq$ RMS of $Z_{\max}$.

Hence,

$$CGx = r \left| \sum_{j=j_{\min}}^{r} \sum_{i=i_{\min}}^{i_{\max}} Z_{(i,j)} = \frac{1}{2} \sum_{j=j_{\min}}^{j_{\max}} \sum_{i=i_{\min}}^{i_{\max}} Z_{(i,j)} \right. \quad (9)$$

$$CGy = c \left| \sum_{i=i_{\min}}^{c} \sum_{j=j_{\min}}^{j_{\max}} Z_{(i,j)} = \frac{1}{2} \sum_{i=i_{\min}}^{i_{\max}} \sum_{j=j_{\min}}^{j_{\max}} Z_{(i,j)} \right. \quad (10)$$

Equation 9 and 10 are used to find the CG coordinate (CGx, CGy) of interesting area. When r is the position between $i_{\min}$ to $i_{\max}$, while summation of $Z_{(i,j)}$ in row of interesting area is equal to half of all in row. And c is considered same with r but it's in term of column. The result of this equation is shown in fig.4. Since RIFD reference in registration procedure are grabbing with normal position and it is uneasy to control each acquisitions RIFD to be in correct pose position and the same pose position every time and everyone. Consequently, it is essential to specify the CG point of standardized RIFD in order to be used as a reference point of every entering acquired RIFD. Nevertheless, according to various experiments it was found that each input RIFD data will have little change in pose position. The adjust of RIFD pose position to standard pose position will contribute more correct data. The RIFD of each input person will be searched for center of gravity position and transformed by geometric transform in order to adjust the CG value closest to the reference CG. This will process the RIFD of every face having the same standard CG position to classify face characteristics by nose tip volume and FCM clustering, consecutively.

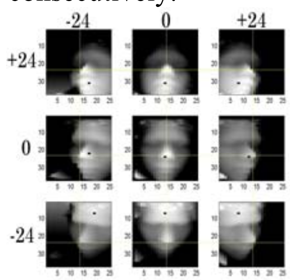

Fig.4 RIFD pose position, black points on each RIFD image shown the CG position.

4.3 Fuzzy C-means

FCM is applied to the invariant range image faces, which have similar features, make cluster and average vector. Each cluster can assign membership to the various data points in each fuzzy set. The steps of classification in this algorithm are as follows :

1. From RIFD database, we can define a family of fuzzy partition matrix , M_{fc} , for the classification involving c classes and n data points,

$$M_{fc} = \left\{ U_{cxn}^{(0)} \mid u_{ik} \in [0,1]; \sum_{i=1}^{c} u_{ik} = 1; 0 < \sum_{k=1}^{n} u_{ik} < n \right\} \quad (11)$$

Where I=1,2, …, c; k = 1,2, …, n and $U_{cxn}^{(0)}$ is a fuzzy c – partition (n data points, c classes) from the each pose of n face images. We fix c (2 ≤ c ≤ n) and initialize the U matrix : $U_{cxn}^{(0)} \in M_{fc}$. Each step in this algorithm will be labeled r, where r = 1,2,…

2. Crate the data matrix in each pose, $X_{n\,x\,z}$, so that it has z elements from each pose of n face images.
3. Calculate the c center:

$$V_{ij} = \frac{\sum_{k=1}^{n} u_{ik}^{m'} . X_{kj}}{\sum_{k=1}^{n} u_{ik}^{m'}} \quad (12)$$

Where j = 1,2,…,m

m is a weighting parameter to control the amount of fuzziness in the classification process.

4. Calculate d_{ik} :

$$d_{ik} = d(x_k - v_i) = \left[\sum (x_{kj} - v_{ij})^2 \right]^{1/2} \quad (13)$$

Where u_{ik} is the membership of the k th data point in the i th class.

5. Update the partition matrix for the r th step, $U^{(r)}$ as follows:

$$u_{ik}^{(r+1)} = \left[\sum_{j=1}^{c} \left(\frac{d_{ik}^{(r)}}{d_{jk}^{(r)}} \right)^{2/(m'-1)} \right]^{-1} \text{ for } I_k = \varnothing \quad (14)$$

or

$$u_{ik}^{r+1} = 0 \text{ for all classes I where I } \in I_k \quad (15)$$

where

$$I_k = \{ I \mid 2 \le c \ge n ;\ d_{ik}^{r} = 0 \quad (16)$$

And

$$\widetilde{I}_k = \{1,2,...,c\} - I_k \quad (17)$$

And

$$\sum_{i \in I_k} \mu_{ik}^{(r+l)} = 1 \quad (18)$$

6. If $\| U^{(r+1)} - U^{(r)} \| \le \varepsilon_L$, stop ; otherwise set r = r+1 and return to step 3.

5 Recognition Procedures

This procedure consists of various block diagrams. Its details are in Ref. number 1.

So, in this paper the researcher will describe the added parts. It is for improvement of the effectiveness of job. The objective of this paper is to focus on two points; application of volume clustering and Membership Matching Search

(MMS) in order to increase pose and person searching velocity for matching process.

5.1 Membership Matching Score (MMS)

The MMS is the technique that enables the model to efficiently classify the differences of the surface slope of RIFD. This technique is based on image base matching, which is quite simple, requiring a small image size. Surprisingly, MMS shows a high correction rate result compared with conventional matching methods [1], due to the requirement that the conventional method uses a larger image size. The MMS special characters can be used to match numerous poses in the multi-pose database.

Additionally, the MMS method calculates the similarities between two data sets. This MMS method is voting by counting number of the memberships in the inner boundary. Voting score is used as the indicator to measure the similarity level. Using the gradient of RIFD results in more accurate classification, and this characteristic of the gradient of RIFD is suitable for the MMS method. The results are better than using normal RIFD, which is not a pure feature. The region between the upper and lower boundary can be seen in Eq.(21).

Define:

$$\overline{f(x_i,y_i)} = f(x_i,y_i)\lfloor f(x_i,y_i) > f^r(x_i,y_i)+\zeta \rfloor \quad (19)$$

$$\underline{f(x_i,y_i)} = f(x_i,y_i)\lfloor f(x_i,y_i) > f^r(x_i,y_i)-\zeta \rfloor \quad (20)$$

$$\underline{\overline{f(x_i,y_i)}} = \sim \overline{f^r(x_i,y_i)} \cap \sim \underline{f^r(x_i,y_i)} \quad (21)$$

and $n\{A\}$ = number of numbers in set A, then score of Membership on inner boundary (similarity score) is shown as the following equation:

$$M = n\left\{ f^t_{(x_i,y_i)} \cap \underline{\overline{f(x_i,y_i)}} \,\middle|\, f^t_{(x_i,y_i)} \in E \wedge f^t_{(x_i,y_i)} \neq 0 \right\} \quad (22)$$

Notation:

$\overline{f(x_i,y_i)}$ = Upper Boundary area.

$\underline{f(x_i,y_i)}$ = Lower Boundary area.

$\underline{\overline{f(x_i,y_i)}}$ = Area between Upper and Lower Boundary.

ζ = gap distance

E = position in elliptic mask boundary

N = number of element in ellipse area

M = number of members in inner boundary

x, y = column and row of image matrix and i = 1 to 156, j = 1 to 108.

$f^r(x_i,y_i)$ is the mean function of reference face, which comprises of the vector of gradient RIFD at the position x_i,y_j of any person number (I) and pose (j). $f^r(x_i,y_i)$ is the mean function of test face, which comprises the vector of gradient RIFD at the x_i,y_j position for any person number (i)

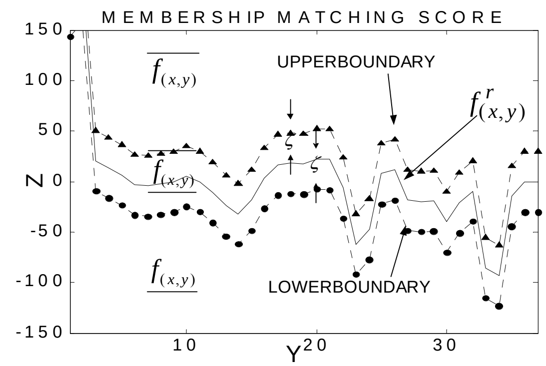

Fig 5. Function with upper boundary and lower boundary

and pose (j). Details of above variables can be illustrated in Fig 5. This figure shows the function $f^r(x_i,y_i)$ with upper boundary $\overline{f(x_i,y_i)}$ and lower boundary $\underline{f(x_i,y_i)}$.

Referring to Eq. (21), M shows the score of smilarity surface of two data sets. Thus, the similarity level can be calculated by Eq.(22)

$$\text{Similarity} = \frac{M}{N} \quad (23)$$

From Eq.(23), when similarity moves toward the number one, this shows the test gradient image and reference image are behaving accordingly. A maximum peak of pose similarity in each record is used to determine the maximum peak for each test subject. This determination can classify an individual test subject, which can then be explained by Eq.(24)

$$\text{Personal Index} = \max(\text{Similarity}(i,j)) \quad (24)$$

where i and j are index similarity of persons (records) and poses (fields) sequence respectively. The field number is the number of generated multi-pose for each test subject. The record number is the number of the test subject that is assigned for face recognition. The altered characteristic of pose (j) gradually changes for every 2 degrees. Thus, the matching search process does not necessarily do the matching for each pose.

6 Experimental and Results

In this experiment, nose tip volume is applied as one of the most important characteristics using in identifying faces. It is found that the memory space required for such scheme is tremendously reduced. Moreover; the experiment shows that FCM gains more than 80 percent of effective recognition rate in 7 identified groups of people, each of which contains 10-25 members. The recognition process time for 130 faces is also found to be speed up by more than [1-2] to 20 times.

7 Conclusion

The result shows that the face recognition rate is effective with more than 80 percent and processing time is also speeding up by more than 20 times. According to the result, it can be concluded that applying nose tip volume as a characteristic using in identifying faces can decrease processing time. Although the recognition accuracy rate is decreasing, it is still considered acceptable with more than 80 percent of effective recognition rate.

In the future, we plan on adding multi-pose images into the database. The face recognition system in the security system is a wide area of application to be applied especially in high security situations such as automatic teller machines, security rooms, automatic safes and confidential information access facilities.

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