Facial Expression Recognition Based on Incremental Isomap with Expression Weighted Distance

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***Abstract*—The Isometric mapping algorithm is an unsupervised manifold learning algorithm, with no consideration of the class of training samples, while supervised isometric mapping treats the difference among classes equally. Considering the inner relationship between different expressions, we have proposed isometric mapping algorithm based on expression weighted distance, which assigns weighted values according to different sample distance in order to make full use of knowledge of expression classes when calculating the geodesic distance between training samples. We use incremental isometric mapping algorithm on new samples so as to simplify computation significantly when dealing with new samples. Then k-NN classifier is applied to classify different expression features. The facial expression recognition experiments are performed on the JAFFE database and the results show that this proposed algorithm performs better than ISOMAP algorithm and supervised ISOMAP algorithm, and it is more feasible and effective.**

***Index Terms*—Incremental ISOMAP; Manifold Learning; Expression Weighted Distance; Facial Expression Recognition**

I. INTRODUCTION

Facial expression is a basic form for humans to deliver their emotions, as well as a substantial way to assist communications. Expressions can be divided into six basic expressions as surprise, anger, disgust, fear, sadness and joy, and one neutral expression, by the psychologist Ekman[1][2]. Extract the feature information of facial expressions, and then classify and try to understand them according to humans' cognitions and thinking mode[7].

Facial image is a high-dimensional data set, so reducing the dimension of the data is essential before carrying out the expression classification[3]. Dimension reduction aims to describe a larger set of data with a smaller feature dataset, by which, the nature structure hidden behind the dataset will be excavated[4]. Classic dimension reduction methods include PCA, ICA and LDA, but they are all linear methods, which are not applicable to high-dimensional facial expression data. Manifold learning, as an efficient dimension reduction method for facial expression dataset, has been used in such aspects as facial recognition, expression recognition and radar recognition[5][6].

Isometric mapping is a widely used manifold learning algorithm, which combines the main spirit of PCA and MDS. It is capable of learning the nonlinear structure of the dataset with its efficiency, global optimization and asymptotic convergence. The traditional isometric mapping algorithm is unsupervised with no consideration on information of the class of samples. Feng proposed a supervised ISOMAP algorithm, which applies class label information as supervised message, that is, mapping the centralized training higher facial information to the lower dimensional manifold space, through which to realize the dimension reduction of initial facial feature information[8]. ZHU trained images by supervised ISOMAP algorithm, clustered based on identity and expression information of images, and obtained good recognition results of identity and expressions[9]. But he did not get the optimal results because of the interfere of identity into the modified formula. Wang Wei applied Procrustes Distance to replace Euclidean distance in the process of constructing neighboring map[10]. ZHANG Yingfeng proposed a method to construct the optimal neighborhood graph against the sensitivity of parameters of ISOMAP, and had a better approximation of the geodesic distance between data points[11]. All the previous work obtains considerable results in the improvement of neighborhood graph and geodesic distance.

To sort a high dimensional facial expression image to one of the six basic expressions by applying the isometric mapping algorithm or its extended algorithms, the dimension should be reduced firstly and the classification standard of the new sample is the low dimensional characteristics. Unlike iterative algorithms,

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isometric mapping and its extended algorithms loop once, which increases the influence of dimension on classification result after dimensional reduction. Tenenbaum mentioned that ISOMAP topology's stability and robustness of noise interference depend on the value of the neighborhood parameter, and proposed a neighborhood parameter selection method based on residuals[17]. We have improved this neighborhood parameter selection method based on residuals and have proposed a dimension selection method based on residual variance. This new method will be used in isometric mapping and its extended algorithms will help to find the optimum dimension.

The supervised ISOMAP algorithm takes the class information into consideration, but treats the difference between classes equally. In facial expression recognition, the difference between expressions is unequal, for example, the difference between happy and sad is much more significant than that between fear and sad. Concerning the various difference, we have proposed a modified supervised ISOMAP algorithm, that is, the ISOMAP with expression weighted distances (EW-ISOMAP). In our algorithm, we assigns according weighted values on different training samples when constructing neighborhood graph so as to get optimal recognition results, making full use of prior expression knowledge. We have carried out experiments on the JAFFE database by this newly proposed method and acquired considerable results.

II. Incremantal Isomap With Expression Weighted Distance

A. Isometric Mapping Algorithm

Suppose there is a dataset with n samples $X=\{x_1,x_2,\ldots,x_n\}$, $x_i \in R_d$, and they are all in the high-dimensional space. The ISOMAP aims to find a low-dimensional mapping $Y=\{y_1,y_2,\ldots,y_n\}$, $y_i \in R_m$, and m<<d to lower the dimension of the high-dimensional data according to certain criteria. The ISOMAP algorithm can be divided into 3 steps:

1. Apply the given data set as the input, and the input is a higher data set. Consider it as a graph and work out k_1 neighbor points of every point in the graph. If x_i and x_j are neighbors, then the distance d(i,j) = $\|x_i - x_j\|$, or it will be ∞;
2. With the Floyd algorithm, compute the shortest distance of each vectors $d_G(i,j)$, and the geodesic distance matrix is
$$D = \{d_G(i,j)\} \quad (1)$$
3. Obtain the lower-dimensional manifold coordinate system. Set S = $\{d_G(i,j)^2\}$, $r(D)$ = -HSH/2, H = $\{\delta_{ij} - 1/N\}$. The lower manifold coordinate of the data set $X=\{x_1,x_2,\ldots,x_n\}$ is Y = $[\sqrt{\tau_1}\cdot\sigma_1, \ldots \sqrt{\tau_d}\cdot\sigma_d]^T$, with τ as the top d maximum eigen values of r(D), σ as the eigen vector accordingly.

The dimension of high dimensional data is d, and it turns to m after dimension reduction with ISOMAP. Considering the great impact of dimension on the classification result, we have proposed a dimension selection method based on residual variance as follows: High dimensional data X turns to a low-dimensional data Y through a dimension reduction process, and Y is a related data set with the low dimension m. That is, the dimensions of Y are different under different values of m. Compute the covariance of original data Y and the Y with landmarks, subtract 1, and then add negative sign to the result, by which we have obtained the curve of the residual variance with the low dimension m. As the curve stabilizes, we take the minimum value of m to be the dimension after dimensional reduction.

B. Incremental Isomap with Expression Weighted Distance

Compared to traditional ISOMAP, the supervised ISOMAP algorithm takes the class information into consideration when seeking for the shortest distance between samples, which makes the distance formula different. The geodesic distance formula of supervised ISOMAP is as follows:

$$d^*G(i,j) = dG(i,j) + \alpha\Lambda \quad (2)$$

dG(i,j) is the geodesic distance between x_i and x_j, with no consideration of class information; $d^*G(i,j)$ is the new geodesic distance concerning the class information of x_i and x_j; Λ is the largest geodesic distance; α is 0 when samples are of one class, or it will be 1.

Supervised isometric mapping algorithm takes class information into consideration. The geodesic distance is used between the same kind of samples and an extra value will be added to the geodesic distance between different class of data. This consideration does not have any error in the two types of samples, but if the sample category increases, there will be an obvious flaw, that is, it cannot explain specific information among classes. In order to make up this flaw, we try to change sample weighted values of different classes, in other words, the distance between samples of different class will plus a fixed weighed value on the basis of the original distance.

A variety of complex expressions are mentioned in books about micro expressions, like complex smile and other human social expressions. Smile can be integrated into negative emotions such as surprise, disgust, anger, fear and sadness, and the formation of surprise, sneer, grinning, fear of laughter and sadness laugh smile come into being. Disgust and fear can form the envy of jealous and hating expression. Sadness and disgust form a complex displeasure of disgust expression. The fears and sadness form a complex expression of an immersive tragedy. All the above indicates the relations between six basic emotions and are all within the scope of micro expression study.

Facial expression recognition is special in pattern recognition with samples related to expressions. The experimental results will be better if the prior knowledge of expressions can be used. Tang did experiments on facial expression images[12]. They divided the personnel into two groups: the Professionals group and the Non-Professionals group. Regarding persons in the Non-Professionals having no experience on facial expression recognition, and persons in the Professionals group having a good understanding on expressions, we choose the results from Professionals group as our reference, as is shown in Table I.

Each column in the table represents the recognition rate of a certain expression which is recognized as other expressions. For example, "happy" expressions are all recognized as "happy" and other expressions have a low recognition rate to be recognized as "happy" recognition; while, "angry" and "fear" expressions have much higher error recognition rates than other expressions. According to figures in Table I, we did modifications on formula (2) in the supervised ISOMAP:

TABLE I.

THE TOTLE RESULTS OF P PROFESSIONALS (%)

	Angr	Disgu	Fear	Joy	Sad	Surpri
Angr	74.55	5.45	8.0	0	3.64	0
Disgu	14.53	81.82	4.0	0	12.72	0
Fear	7.27	0	74.0	0	0	9.09
Joy	0	0	0	100	1.82	1.82
Sad	3.64	12.72	10.0	0	81.82	0
Surpri	0	0	4.0	0	0	89.09

$d^*G(i,j)=dG(i,j)+p(c_i,c_j)\,\alpha\ \Lambda$ (3)

$p(c_i,c_j) \in [0, 1]$ is the modified distance of c_i and c_j, which is only related to expression classes. The matrix made up by $p(c_i,c_j)$ in our experiments is as follows:

$$P=\begin{bmatrix} 0 & 0.2 & 0.9 & 1 & 0.1 & 0.9 & 1 \\ 0.2 & 0 & 1 & 1 & 0.1 & 0.8 & 1 \\ 0.9 & 1 & 0 & 1 & 0.1 & 0.8 & 0.9 \\ 1 & 1 & 1 & 0 & 0.1 & 1 & 1 \\ 0.1 & 0.1 & 0.1 & 0.1 & 0 & 0.1 & 0.1 \\ 0.9 & 0.8 & 0.8 & 1 & 0.1 & 0 & 1 \\ 1 & 1 & 0.9 & 1 & 0.1 & 1 & 0 \end{bmatrix}$$

In the $p(c_i,c_j)$ matrix, small values represent the nearer distances, correspondingly with a higher error recognition rate, while larger values indicate higher recognition rate. For example, the value between "sad" and "surprise" is large, indicating a large distance and a high recognition rate. Expressions in the $p(c_i,c_j)$ matrix are "Angry", "Disgust", "Fear", "Happy", "Neutral", "Sad" and "Surprise" consequently.

By changing the formula of geodesic distance in the ISOMAP algorithm, the relationship and class information of expressions are applied to the geodesic distance calculation, which can help to find nearest neighborhood and ensure that same type of expression samples are closer and different types of expression samples locate at different distance locations. At last, traditional MDS algorithm is used to calculate the eigenvalue and eigenvector, and the obtained low dimensional feature keeps the inherent feature constant. The training sample set is mapped to low-dimensional manifold space and the low dimensional features are obtained as the basis of classification.

The EW-ISOMAP algorithm is not applicable in dynamic environment. When a new sample is added to the sample set, because of the uncertainty of new sample's class information, this method cannot be used to reduce the dimension of the new sample. Dongfang Zhao proposed the Incremental ISOMAP algorithm to enable the ISOMAP to adapt to the changing circumstances[13][14]. LIU Qian worked out the k-neighborhood incremental ISOMAP as follows[15][16]: there is a dataset $X=\{x_1,x_2,\ldots,x_n\}$, $x_i \in R_d$, and Y is the lower-dimensional character of it by ISOMAP. Suppose x_{N+1} are the new data points, and Y_{N+1} are the lower-dimensional dataset using the k-neighborhood incremental ISOMAP algorithm. Specific steps are as follows:

1) Calculate the neighborhood dataset of the new data points x_{N+1} and construct the neighborhood graph;
2) Compute the geodesic distances of x_{N+1} and other data points and get the shortest distance $D_{GN+1} = \{d_G(x_i,x_{N+1})\}$;
3) Referring to Step 3 of the Incremental ISOMAP, compute the lower-dimensional y_{N+1} from x_{N+1}.

$$y_{N+1}=[\frac{1}{\sqrt{\tau_1}}\sigma_1^T F,\frac{1}{\sqrt{\tau_2}}\sigma_2^T F,\ldots,\frac{1}{\sqrt{\tau_{d1}}}\sigma_d^T F]^T \quad (4)$$

$$F=[f_1,f_2,\ldots,f_N]^T \quad (5)$$

$$2f_i=\frac{1}{N}\sum_{i=1}^{N}d_G^2(x_i,x_{N+1})-\frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}d_G^2(x_i,x_j)+\frac{1}{N}\sum_{j=1}^{N}d_G^2(x_i,x_j)-d_G^2(x_i,x_{N+1}) \quad (6)$$

The low dimensional feature of new samples can be recognized through static approaches. Static classifiers such as support vector machines(SVM), naïve Bayes(NB), tree-augmented naïve Bayes(TAN), and k-nearest neighborhood(k-NN) attempt to recognize facial expressions using one frame image. Among these static classifiers, the k-NN classifier shows the best classification result[18][19]. And the k-NN classifier is applied to recognize the new sample in our experiments.

III. EXPERIMENT RESULT

We have realized facial expression recognition based on EW-ISOMAP algorithm with the help of MATLAB 7.6. In order to verify the validity of the EW-ISOMAP algorithm, we have done experiments using the JAFFE facial expression database and compared the results with ISOMAP and S-ISOMAP. The JAFFE database is consist of 213 expression images from 10 persons, with 7 kinds of expressions.

Fig. 1. Sample images of the employed JAFFE facial expression database

Firstly, we use this database to verify the effectiveness of our proposed algorithm. The sequences of nine people are used as the training samples and the left are treated as the testing samples. We repeat it 6 times and the testing people are selected randomly each time.

With regard to training samples, we must firstly determine the dimension after dimension reduction and use the proposed parameter selection method based on residual variance. Figure II below shows the residual variance curve with the change of dimension. In the lower dimension, the residual variance is large. As the dimension increases, the residual variance continuously becomes small. When the dimension is 11, the residual variance reaches a minimum value. With a further increase of the dimension, the residual variance will not change any longer. Therefore, we choose 11 as the value of dimension after dimension reduction. When the sample size of the training set changes, similarly, the proposed method is employed to determine the value of the lower dimension. The following table lists the dimension values at different number of samples based on residual variance.

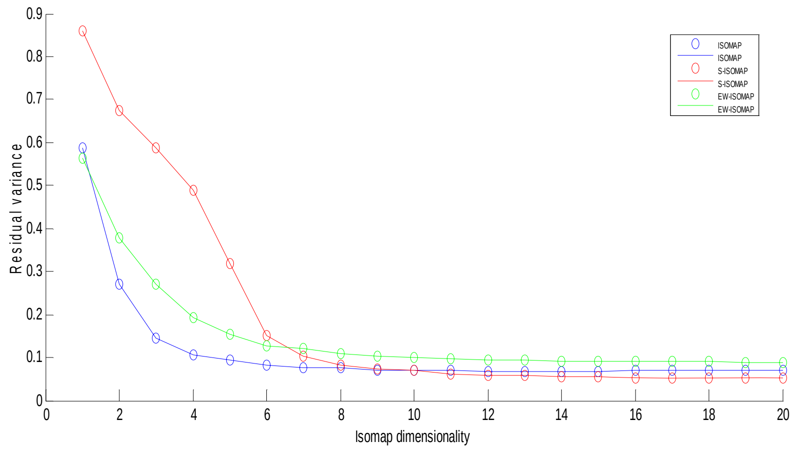

Fig. 2 Residual Variance with different Isomap dimensionality in the EW-ISOMAP algorithm

TABLE II

DIMENSION VALUE WITH SIZE OF TRAINING SAMPLE IN THE EW-ISOMAP ALGORITHM

Size of Training Sample	30	50	70	90	110	130	150	170	190
ISOMAP	5	7	6	3	5	6	7	9	11
S-ISOMAP	7	8	7	9	10	10	12	11	11
EW-ISOMAP	8	8	8	9	9	10	10	11	11

Fig. 3, Fig. 4 and Fig. 5 show the clustering results of 7 kinds of expressions from 9 persons using the EW-ISOMAP algorithm, supervised ISOMAP algorithm and unsupervised ISOMAP respectively. The feature obtained by using EW-ISOMAP algorithm can be distinguished very easily. Two of the seven expressions stay close, and other expressions lie far. The cluster result of expression feature by using supervised ISOMAP is worse and not all the features can be separated well. The cluster result by using unsupervised ISOMAP is the worst and all the features gather together in disorder. From all the images, the result using EW-ISOMAP is the best, which proves the effectiveness of our proposed algorithm.

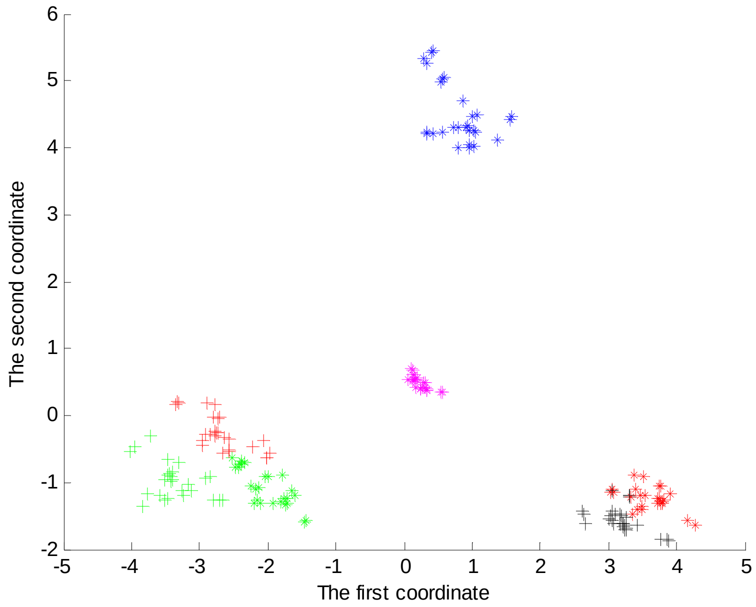

Fig. 3 The cluster result of expression images of nine subjects using EW-ISOMAP algorithm visualized with the first and the second coordinate of 11 dimensions.

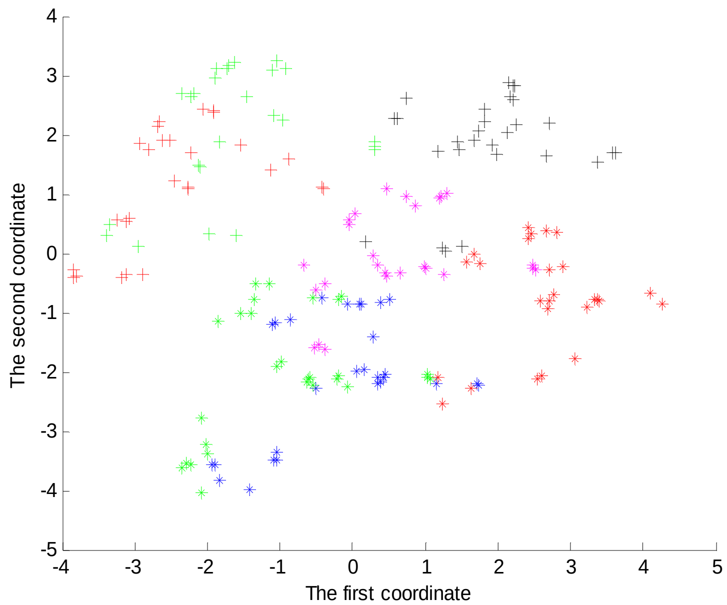

Fig. 4 The cluster result of expression images of nine subjects using supervise ISOMAP algorithm visualized with the first and the second coordinate of 11 dimensions.

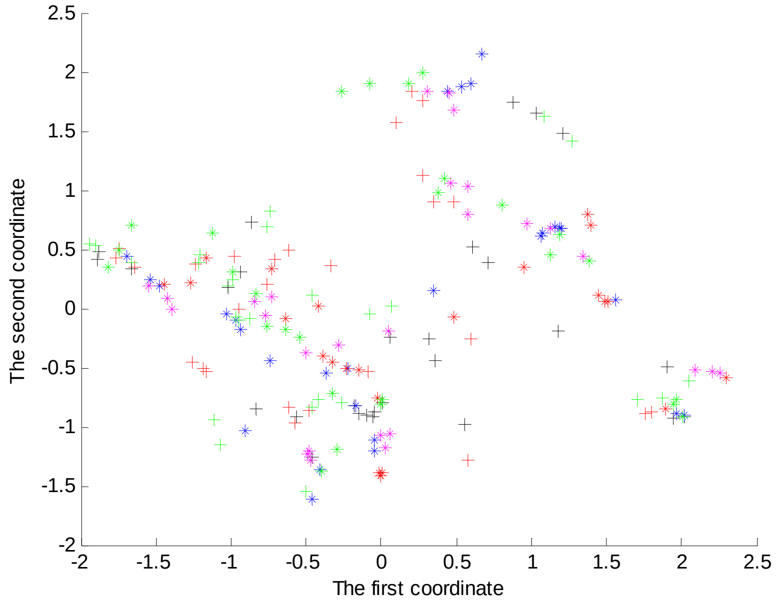

Fig. 5 The cluster result of expression images of nine subjects using unsupervised ISOMAP algorithm visualized with the first and the second coordinate of 11 dimensions.

Table III shows the final result when nine subjects are treated as training samples. From the table, we can see that not all of the recognition rates is high. But the recognition rates are higher than those computed by the other two algorithms, which implies the efficiency of our proposed algorithm.

The k-nearest neighborhood classifier is employed to recognize new sample. The k value is the only and an important parameter of the classifier. We use nine subjects as the training set and one as the test set. The value of k is from 1 to 50 and ISOMAP, S-ISOMAP and EW-ISOMAP algorithms are used to reduce the dimension of the samples. Figure 6 is the result of experiment. The smaller the value of k is, the lower the facial expression recognition rate is. The rate increases with the value of neighbor within a certain range. When k equals 20, the rate reaches the maximum and stays stable. As a result, the optimum value of k is from 20 to 45.

Then we use this database to perform the person-independent tests. All the sequences of one kind of expression from 10 persons are divided into training and testing sequences. At first, nine persons are used as training samples and the left one person is treated as testing sample, 10 cycles like this. Then eight persons are used as training samples and the left two are treated as testing samples, 10 cycles like this. Eventually, five persons are used as training samples and the left five are used as testing samples, 10 cycles like this. It means that the number of training people is from nine to five and the relative number of testing people changes from one to five. During the stage, all the training samples are selected randomly. Fig.7 shows the facial recognition rate with the number of the training samples based on ISOMAP, S-ISOMAP and EW-ISOMAP. It shows that our proposed algorithm outperforms the others and the recognition result become more accurate as the number of training people increases.

TABLE III.

THE RECOGNITION RATE OF ALL THE EXPRESSIONS USING THREE ALGORITHMS WHEN NINE SUBJECTS ARE TRAINING SAMPLES.(%)

	Angry	Disgust	Fear	Happy	Neutral	Sad	Surprise	Ave.
ISOMAP	77.8	78.3	76.2	88.8	91.7	87.5	85.0	83.6
S-ISOMAP	84.0	84.0	79.1	88.9	95.8	92.3	86.7	87.3
EW-ISOMAP	90.1	93.8	89.5	96.8	99.8	96.2	92.3	94.7

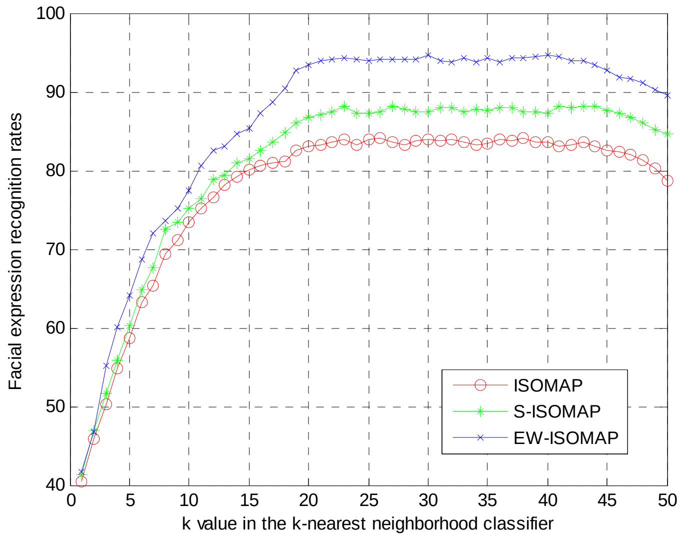

Fig. 6 The change of the facial expression rate with the k value in the k-nearest neighbor classifier

IV. CONCLUSIONS

We have proposed supervised ISOMAP algorithm with expression weighed distances, which is used in higher dimensional facial expression images and is applied to facial expression recognition in this paper. This algorithm makes full use of the prior knowledge of expressions on basis of supervised ISOMAP and extracts significant facial features by reducing the dimensions of higher dimensional expression database. The expression features of the training images can be well clustered in our experiment. Then the lower dimensional mapping of a test sample will be classified to be one of the seven basic expressions using k-NN classifier. Our proposed algorithm shows a better performance than unsupervised ISOMAP and supervised ISOMAP in the JAFFE database, which indicates the effectiveness of the algorithm.

P values are determined from previous expression research results, combined with my own understanding of expression, with a certain degree of subjectivity. Moreover, there are no quantitative results indicating the relationship between various expressions, so more experiments are essential to find out the intrinsic link between various expressions in order to make the P value perfect.

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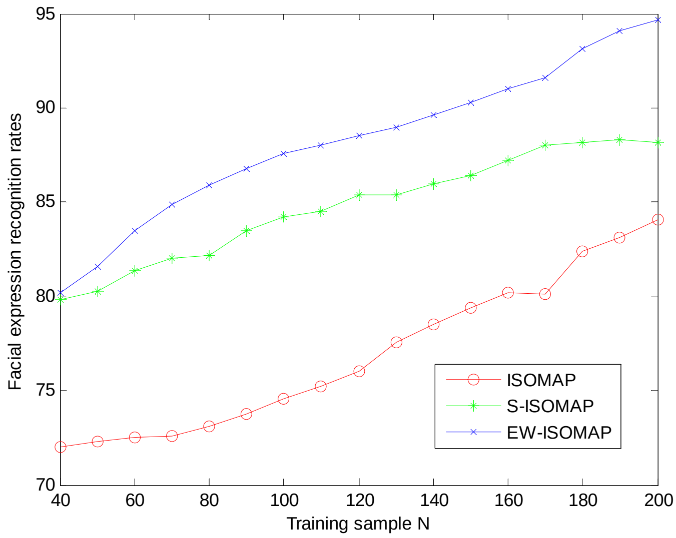

Fig. 7 The change of the facial recognition rate with the number of training sample.

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