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Multi-view Ear Recognition Based on B-Spline Pose Manifold Construction

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***Abstract* - In this work, multi-view ear recognition problems are examined in detail. A new multi-view ear recognition approach based on B-Spline pose manifold construction in discriminative projection space which is formed by null kernel discriminant analysis (NKDA) feature extraction is presented. Many experiments and comparisons are provided to show the effectiveness of our multi-view ear recognition approach.**

***Index Terms* - Ear biometrics, Multi-view ear recognition, Pose manifold, B-Spline**

I. INTRODUCTION

Ear recognition is a new rising biometrics trend recently. Since ear has some desirable properties such as universality, uniqueness, and permanence [1], ear recognition is expected to be a creditable technique of human identification.

In recent years, there have appeared some biometrics techniques which utilize 2D intensity images for ear recognition [2] [3] [4]. All these methods only use single front view for ear recognition. However, the imaging of ear shape is always affected by the rotation of human head. When subject's ear is captured in different views between training samples and test samples, it will result in matching failure. In addition, Ping Yan [5] and Hui Chen [6] propose 3D ear recognition techniques respectively. Although both of them report good 3D recognition performance, the cost of 3D range scan device will be higher than that of 2D capturing device. In addition, these 3D recognition techniques need an additional 2D registered color image with ear range image. Thus, upon the deficiency of current ear recognition ways, it is natural to turn to pursuit a multi-view ear recognition system.

Ear multiple views contain ear different orientation shape features which can be well utilized for discrimination. Moreover, stimulated by Simon J.D's hint [7] on face recognition across large pose changing, ear multiple views can be treated as a smooth trajectory which is formed by projecting ear to certain subspace termed as ear manifold, which can be illustrated as Fig. 1. It suggests us that ear pose manifold in feature space plays its role in a curve way. In this work, null space kernel discriminate analysis (NKDA) [8] is adopted to form ear multi-view discriminative feature space and use B-Spline interpolation to construct ear pose manifold for recognition.

The contributions of our work include: (1) A new multi-view ear recognition method based on NKDA feature extraction and B-Spline pose manifold construction is presented. (2) Abundant experimental results and comparisons between ours and other methods on our multi-view data set are provided.

The rest of this paper is structured as follows. In Section II, multi-view ear sampling system is firstly introduced. Then, the flowchart of our multi-view ear recognition procedure is provided. In Section III, the technique details of the multi-view ear recognition based on NKDA feature extraction and B-Spline pose manifold construction are presented. In Section IV, some ear recognition experiments and comparisons are given. Finally, short discussions and conclusions are made in Section V.

II. MULTI-VIEW EAR RECOGNITION SCHEMA

In this section, multi-view ear sampling system and multi-view ear data set are introduced firstly. Then, the flowchart of recognition procedure is provided.

A. Multi-view Ear Sampling

A low cost ear sampling system uses one high resolution (1280×1024) camera to capture ear multi-view images. The whole sampling device is placed in a dark room and is illuminated with fixed lighting. We utilize a half-circle orbit to control camera moving to the specified angles from the location 0°. Moving camera with different angles, multiple pose ear images are obtained and they naturally become ear multi-views. In this paper, ear's ten views ($-90^{\circ},-60^{\circ},-50^{\circ},-40^{\circ},-20^{\circ},0^{\circ},+20^{\circ},+40^{\circ},+60^{\circ}+90^{\circ}$) are captured. However, since the ear appearances in -90^{o} and $+90^{o}$ views are not integrated, such views are not used for following processing in practice. Totally, 60 individuals' right ears are

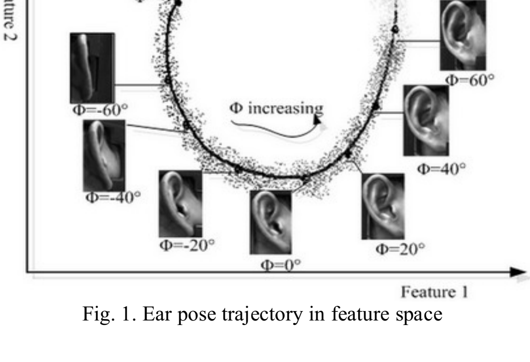

Fig. 1. Ear pose trajectory in feature space

sampled and 600 sampled images (ten views per individual) are acquired. Ear are segmented by manual supervising from original images and the segmented ear images are saved as multi-view ear data set. Finally, there are 60 individuals, and each individual has eight multiple views $(-60^o, -50^o, -40^o, -20^o, 0^o, +20^o, +40^o, +60^o)$ in our data set. The size of each view image is 134×255. As an example, Fig. 2 shows ten ear individuals' multiple views and the views of each individual turn from -60^o into 60^o gradually.

B. Flowchart of Multi-view Ear Recognition Procedure

Our multi-view ear recognition scheme holds two main steps: NKDA feature extraction and B-Spline pose manifold construction. Fig. 3 shows the flowchart of such procedure. In training stage, NKDA method is implemented on training samples to extract features which are used to construct the discriminative feature space. Then training samples are projected onto the feature space to generate projected points at different positions in the space. Since the training and test samples are in different views, they should not be matched directly. Alternatively, we choose B-Spline for views' interpolation for all projected points. Once the views' Interpolation for all projected points is completed, the pose B-Spline curve of each subject is acquired. And theoretically,

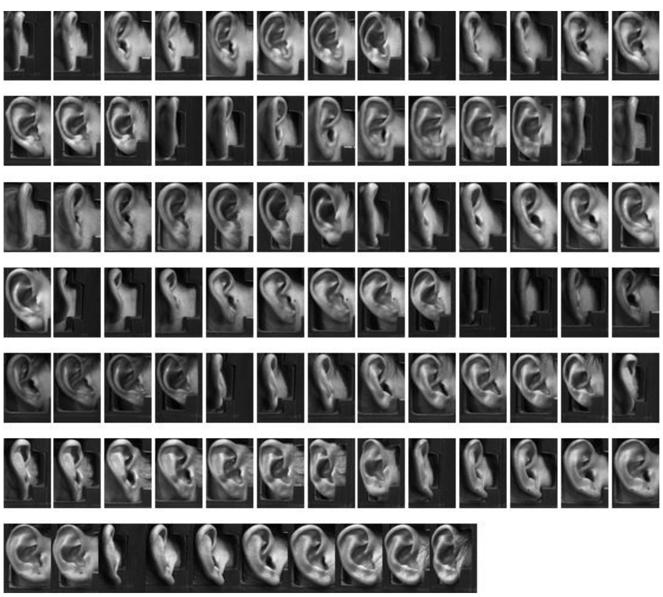

Fig. 2. Ten ears' multiple pose samples

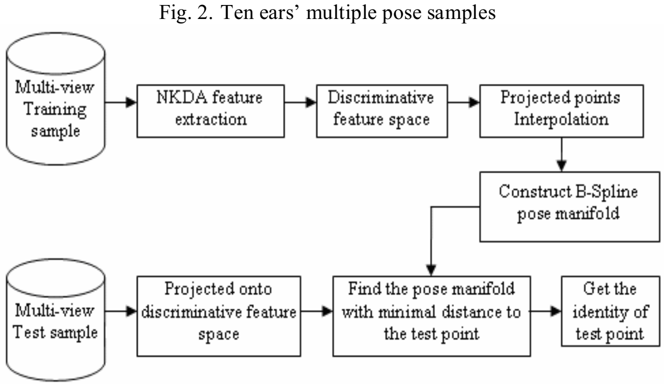

Fig.3. Flowchart of multi-view ear recognition procedure.

different subjects hold different pose B-Spline curves which represent different pose manifolds. In this way, a few of new views of each subject are generated which are denoted by new projected points in the discriminative feature space.

In the test stage, one test sample is projected onto the discriminative feature space firstly. Then, the distance of test point to all existing points of B-Spline pose manifolds is calculated. And the subject of certain pose manifold which has the minimal distance to the test point in this space is recognized as its identity.

III. TECHNIQUE DETAILS

In this section, a new multi-view ear recognition approach based on ear samples statistical learning and B-Spline pose manifold construction is provided. The ear multiple pose manifold is deducted firstly. Then null space kernel discriminate analysis (NKDA) is used to extract multiple pose non-linear features. Finally, B-Spline is made use to construct pose manifold explicitly in NKDA discriminative feature space for ear recognition.

A. Multi-view Ear Pose Manifold Deduction

In human vision system (HVS), human vision can capture ear discriminative features and utilize the continuity of ear pose trajectory to recognize ear in different perspective. This suggests us two hints: discriminative feature and manifold continuity. Moreover, in recent work [7] [9] [10] [11] [12], face varieties of subjects, with lighting fixed, can be regarded as a 2D manifold which contains and represents face pose variation and facial expression changing. However, since ear expression does not exist, the variability is simpler – only pose variation can take place. In this paper, ear multiple pose images are acquired by rotating camera horizontally, which means there is only one freedom degree in motion and such motion leads to one dimension trajectory. Meanwhile, Yongming Li [9] utilize a set of view planes to approximate the identify surface for discriminating face classes. According to shape deduction of ear pose manifold, Yongming Li's view planes is replaced with one dimension smooth pose curve in NKDA discriminative feature space for ear recognition. This approach also happens to satisfy the requirement of continuity of pose manifold.

Suppose multi-view ear samples are projected to certain feature space in which the dimension is d and suppose x_i is one arbitrary projected pose sample, i.e., $x_i \in IR^d$, and y_i is the true pose location of this sample in the feature space. From a statistical learning point of view, ear pose manifold (one dimension curve) construction can be regarded as one dimension pose location regression problem, e.g., finding one pose location regression function with constrains on smoothness and low variance to minimize the penalized residual sum of squares (RSS) via least squares method:

$$\arg\min_f RSS(f,\lambda) = \sum_{i=1}^{N} (y_i - f(x_i))^2 + \lambda \int (f''(t))^2 \, dt \qquad (1)$$

where $f(x)$ denotes pose location regression function, N is the number of samples. The penalty term $\int (f''(t))^2 \, dt$, weighted by smoothing parameter λ, forces smoothness on the function whereas the data fidelity measure term $\sum_{i=1}^{N}(y_i - f(x_i))^2$ would make it rough so as to mimic the data. Remarkably, it shows that (1) has an explicit unique solution which is a natural cubic spline with knots at each $x_i, i = 1...N$ [13]. This approach is also called "spline smoothing" procedure. Thus, with using linear basis expansion, the regression function $f(x)$ can be denoted by:

$$f(x_i) = \sum_{m=1}^{M} \beta_m h_m(x_i) \tag{2}$$

where $f(x_i)$ is an pose location estimation for x_i, $h_m(x)$ is a spline basis function, β_m is the coefficient of spline basis function or parameter of the regression model, and M is the number of basis functions. In the case of cubic B-Spline pose regression, the spline order M is four and the final constructed pose manifold is second order continuous. In Part C B-Spline pose manifold construction method will be shown in detail

B. Extracting Multi-view Ear Non-linear Features by NKDA

Since multi-view ears are severely non-linear, in this work, Null Space Kernel Discriminate Analysis (NKDA) is adopted to extract the non-linear ear discriminative features across multiple views. The details of NKDA can be found in [8]. The follows give a short explanation from LDA to NKDA.

Suppose that a set of n samples of d dimension $x_1, x_2, ..., x_n$ belongs to c classes of ear. The optimal projection direction W will be obtained from the following:

$$W = \arg\max_W \arg(W^T S_B W / W^T S_W W) \tag{3}$$

$$S_B = \sum_{i=1}^{c} n_i \left(m^{(i)} - m\right)\left(m^{(i)} - m\right)^T \tag{4}$$

$$S_W = \sum_{i=1}^{c} \left(\sum_{j=1}^{n_i} (x_j^{(i)} - m^{(i)})(x_j^{(i)} - m^{(i)})^T \right) \tag{5}$$

where m is the total sample mean vector, n_i is the number of samples in the ith class, $m^{(i)}$ is the average vector of the ith class, and $x_j^{(i)}$ is the jth sample in the ith class. S_W is called the within-class scatter matrix and S_B is called the between-class scatter matrix. If S_W is a non-singular matrix, the optimal projection vectors W will be the eigenvectors of $S_W^{-1} S_B$. Unfortunately, if the number of samples is much smaller than the dimension of samples space, S_W will be singular. Seeing that, one substitute- null space based LDA (NLDA) [14] was proposed. In this method, the optimal projection W should satisfy:

$$W^T S_W W = 0, W^T S_B W = I \tag{6}$$

This equation means the optimal discriminative vectors must exist in the null space of S_W. Assuming the dimension of samples in input space is R^n, the main idea of Kernel Discriminate Analysis (KDA) is to solve LDA problem by mapping the input space to a high dimension feature space F by a kernel trick:

$$\phi : x \in R^n -> \phi(x) \in F \tag{7}$$

in which the corresponding kernel function is

$$K(x, y) = (\phi(x) \cdot \phi(y)) \tag{8}$$

With this definition, any two vectors inner product can be easily worked out based on a kernel function so that it needs not to know the feature mapping function ϕ explicitly. Based on kernel function, NLDA can be extended to NKDA [8] which will hold stronger potential both on non-linear feature extraction and class discrimination. Assuming the number of samples is N, the number of total classes is c, the dimension of input space is n, the kernel function is $K(x, y)$, and the output non-linear dimension reduction mapping is Γ, the main steps of NKDA are as follows:

Step1. Compute Kennel mapping matrix on every training sample:

$$K(x_i, x_j), i = 1...N, j = 1...N.$$

Step2. Calculate every class mean and within-class scatter matrix:

$$m_j = \sum_{i \in C_j} K(x_i) / N_j,$$

$$K_w = \sum_{j=1}^{c} \sum_{i \in C_j} (K(x_i) - m_j)(K(x_i) - m_j)^T$$

Step3. Extract the null space P of K_w such that $P^T K_w P = 0$. P is usually in $(N-1) \times (c-1)$.

Step4. The output mapping on the sample set is: $\Gamma(x) = (P^T K) \cdot (x) = P^T \cdot K(x)$.

However, in kernel methods, all formulas are deducted based on the assumption: $\sum_{i=1}^{N} \phi(x_i) = 0$. Actually, owing to lacking explicit function ϕ, following equation is always used to obtain centered kernel matrix:

$$\tilde{K} = K - (1/N) I_N K - K\{1/N\} I_N + (1/N^2) I_N K I_N \tag{9}$$

To observe ears' multi-view appearance varieties in certain feature space, PCA and NKDA are used to extract multi-view ear features respectively. The results are shown in Fig. 4 and Fig. 5. For the sake of conciseness, only patterns of three ear classes are shown here. In Fig. 4 (a), the horizontal numbers (number 1 to number 8) represent the pose indexes from -60° to $+60^\circ$ $(-60^\circ, -50^\circ, -40^\circ, -20^\circ, 0^\circ, +20^\circ, +40^\circ, +60^\circ)$.

NKDA is applied to extract non-linear features of ear patterns of the same classes as shown in Fig. 5. There are three popular kernel functions, and the RBF (Gauss) kernel is adopted as:

$$K(x, y) = (\phi(x) \cdot \phi(y)) = \exp(-\| x - y \|^2 / \sigma^2) \tag{10}$$

where σ is set to1000 in our experiments. The variations and patterns distribution is shown in Fig. 5. Compared with the re-

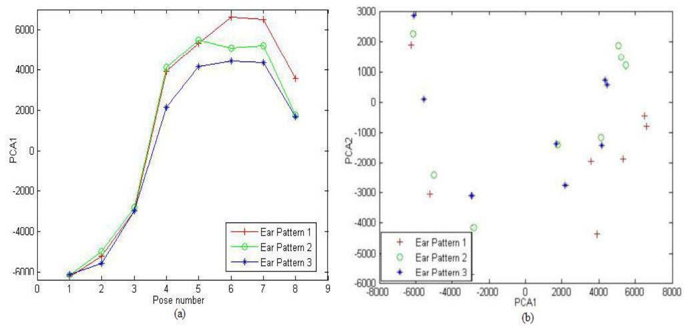

Fig. 4. Ear multiple pose patterns variations in different PCA dimension representation. (a) Variations respect to pose change using 1st PCA dimension. (b) Ear Pattern distribution in first two PCA dimensions.

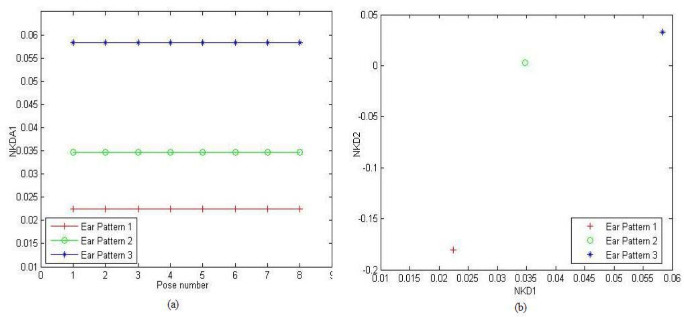

Fig. 5. Ear multiple pose patterns variations in different NKDA dimension representation. (a) Variations respect to pose change using 1st NKDA dimension. (b) Ear Pattern distribution in first two NKDA dimensions.

sults of the PCA patterns in Fig. 4, the separability of different ear patterns in NKDA is much stronger than whatever in one-dimension or in two-dimension. Moreover, Fig. 4 (a) and Fig. 5 (a) show that different ear multiple pose patterns are subjected to certain same distribution model which validates our deduction that ear multiple pose should lie in certain similar manifold. In addition, in PCA analysis, the separability of different pose patterns is very different. For example, in PCA dimension one, ear pattern which lies on $+20^\circ$ pose (number 6) is easier to be separated than those patterns whose poses are before -40° (number 3).

C. Constructing Discriminative B-Spline Pose Manifold

According to pose shape deduction in Part A and figures' validation in Part B, ear multiple poses distribution should lie in one dimension manifold- one kind of curve in feature space. Therefore, if the curve which represents ear poses manifold is constructed explicitly, the full distribution of all ear poses will be acquired. In most cases, existing ear poses are not consecutive and they need to be interpolated to form a continuous and smooth pose curve (see the illustration in Fig.1). From (1) and (2), the optimal pose regression function is natural cubic spline. Among all forms of cubic spline, thanks to B-Spline good characteristics [16], cubic B-Spline is used to construct pose manifold so as there are more than three control point poses (this requirement is not rigorous). Then the category of unknown ear can be determined by ransacking all ears' pose manifolds. Suppose the pose manifold C_p for each individual ear p is known, then the recognition can be formally defined as: for a probe ear view I, the identity p^* can be determined by ransacking all pose manifolds to find the manifold C_p with minimal "distance" to I, i.e.

$$p^* = \arg\min_p d_f\left(I, C_p\right) \tag{11}$$

where d_f represents Hausdorff distance between image I and C_p in feature space. Let $x \in C_p$ denote a point on a manifold C_p and x^* is the point on C_p which is closest to I (i.e. at minimal distance) in Hausdorff distance, then $d_f\left(I, C_p\right) = d\left(I, x^*\right)$ where $d(\cdot,\cdot)$ denotes the corresponding distance. This procedure can be illustrated in Fig. 6 (a). Moreover, in feature space, different manifolds C_p and C_q should be distinctive as much as possible, otherwise some probe images will be confused in determining their identities. This difficulty is shown in Fig. 6 (b). Under this consideration, NKDA is applied to extract ear multi-view features to construct discriminant pose manifold. Since B-Spline has many good merits, then in feature space cubic B-Spline is taken to interpolate pose manifold C_i. Given four control points P_0, P_1, P_2 and P_3, parametric cubic B-Spline curve can be constructed as:

$$Q(t) = \frac{(1-t)^3}{6}P_0 + \frac{3t^3 - 6t + 4}{6}P_1 + \frac{-3t^3 + 3t^2 + 3t + 1}{6}P_2 + \frac{t^3}{6}P_3 \tag{12}$$

If there are more than four pose control knots, then B-Spline curves with more than one parametric can be constructed to approximate pose manifold. Suppose there are N individuals $X_1, X_2 \ldots X_N$, every individual has t(t $\geq$ 4) available training pose, our discriminative pose manifolds can be constructed according to the following steps:

<u>*Step1.*</u> Get projections of t pose of one individual ear in feature space which is extracted by NKDA or PCA, etc. Assuming the dimension of feature space is d.

<u>*Step2.*</u> In feature space, fit d cubic B-Spline curves according to (12) by using every dimension coordinate of projections. Then a set of cubic B-Spline curves M_i which represent one individual ear pose manifold is acquired.

<u>*Step3.*</u> When one probe image X enters, project it to the feature space extracted by NKDA or PCA. Then ransack all constructed pose manifolds C_i according to (11) and find the closest manifold C_p. Thus the identity of X can be declared.

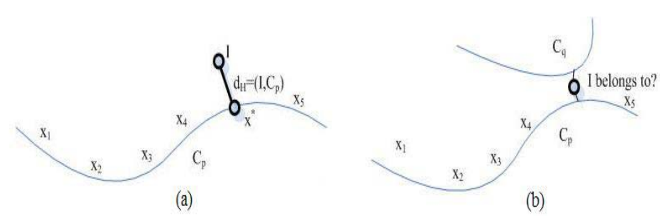

Fig. 6. Pose manifold and image points pose distribution. (a) Distance from an image point to one pose manifold. (b) Difficulty for identify ear when two pose manifolds are close too much

IV. Experiments and Comparisons

A. *Experiments using NKDA and B-Spline Pose Manifold*

To show NKDA discriminating performance, some recognition experiments are made and compared with those stated methods. Our experiments are done on our multi-view ear data set and ear individuals are chosen randomly. Each individual ear has eight multi-view samples. In the test, five views $(-60^\circ,-50^\circ,-20^\circ,+20^\circ,+60^\circ)$ are treated as training samples and the left views $(-40^\circ,+0^\circ,+20^\circ)$ are taken as test samples. This test way is called interpolation test. Some recognition contrasts of different subject numbers are shown in TABLE I. Since PCA only uses 1st-order eigen features to describe low-passed properties of ear images, it is combined with 2rd-order eigenear to improve recognition performance. More details on 2rd-order eigen features can be found in [15]. Fig. 7 shows a plot of error rate versus dimensionality reduction for all 60 ear subjects. It can be seen NKDA gets best recognition rate up to 97.2% and the error rate of NKDA method decreases very fast as dimensionality of ear subspace increases.

Based on the same experimental conditions, B-Spline pose manifold is applied in NKDA, PCA, and KPCA feature space to enhance the performance of ear identification. In addition, cubic polynomial curves and cubic Bezier curves are also tested for pose manifold construction. However, there are certain drawbacks in such kinds of curves which will lead to degrading the shape of pose manifold. With using polynomial or Bezier curves, the recognition performance drops down (see TABLE II). Fig. 8 shows a plot of error rate versus dimensionality reduction in PCA, KPCA, and NKDA methods combined with B-Spline. TABLE II and Fig. 8 indicate that with B-Spline manifold the performances of every recognition method are improved. This is most likely because B-Spline curve actually approximates the true pose manifold of ear individuals. Among them, PCA performance is greatly improved whereas NKDA is slightly lifted. The reason may be that the discriminating power between ear classes has been developed enough by null space, which leave the room of performance improving is less when using B-Spline interpolation.

TABLE I
Recognition Contrasts in Interpolation Test

Methods	Object numbers	Recognition rate
PCA	10, 30, 60	86.7%, 82.2%, 75.6%
PCA+2rd Eigenear	10, 30, 60	86.7%, 83.3%, 80.6%
KPCA	10, 30, 60	86.7%, 83.3%, 75.0%
KPCA+2rd Eigenear	10 ,30, 60	90.0%, 86.7%, 76.7%
LDA	10, 30, 60	96.7%, 88.9%, 87.3%
NKDA	10, 30, 60	96.7%, 97.8%, 97.2%

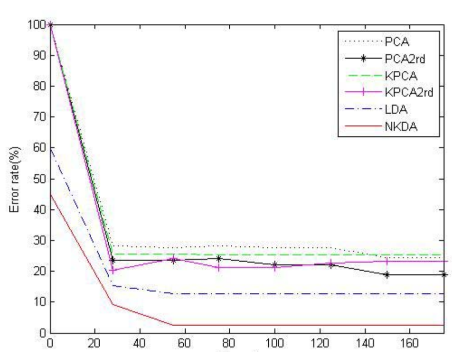

Fig.7. Recognition error rate versus dimensionality reduction.

TABLE II
Recognition Contrast with Pose Manifold

Methods	Object numbers	Recognition rate
PCA+B-Spline	10, 60	96.7%, 95.4%
KPCA+B-Spline	10, 60	90.0%, 89.4%
NKDA+B-Spline	10, 60	96.7%, 97.7%
PCA+polynomial curve	10, 60	83.3%, 81.7%
KPCA+ polynomial curve	10, 60	80.0%, 75.6%
NKDA+polynomial curve	10, 60	93.3%, 95.0%
PCA+ Bezier curve	10, 60	86.7%, 85.0%
KPCA+Bezier curve	10, 60	83.3%, 81.1%
NKDA+Bezier curve	10, 60	96.7%, 97.2%

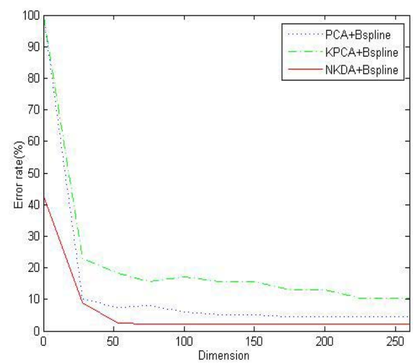

Fig. 8. Recognition error rate versus dimensionality reduction in PCA, KPCA, NKDA

B. *Comparisons With Manifold Learning Methods*

Manifold learning is a kind of non-linear dimension reduction technique which tries to contain local or global relationship among sample points in high dimension space and map them onto low dimension manifold. There are many manifold learning methods, such as LLE [17], Isomap [18], Laplacian Enginemap [19], LPP [12], etc. For face recognition, most of these methods are applied to "learn" or "acquire" intrinsic relationship for different face pose changing and facial expression variation of the same individuals. Obviously, these techniques can be applied to multi-view ear recognition.

The difference between manifold learning and B-Spline pose manifold construction is apparent. Our method constructs pose manifold explicitly by B-Spline interpolation whereas manifold learning mechanism acquires shape characteristics of pose manifold implicitly by "learning". And In manifold learning, local geometry properties are subjected to the definition of neighbors and proximity relationship. Whereas in B-Spline manifold, the locality is related to four control points (four pose) and the continuity and smoothing between different poses are also kept well by good traits of B-Spline.

To make comparison, experimental results are proved in TABLE III. The experimental conditions are consistent to

TABLE III
RECOGNITION CONTRAST TO LLE AND LPP IN INTERPOLATION TEST

Methods	Dimension embedded	Neighbours number	Subject numbers	Recognition rate
LLE	22	35	60	65.6%
Supervised LPP	59	N/A	60	81.1%
Unsupervised LPP	53	18	60	69.4%
NKDA+B-Spline	59	N/A	60	97.7%

previous experiments in Part A. Two manifold learning methods-LLE [17] and LPP [12] are chosen as representatives. Since LLE is non-linear method, a scheme similar to that described in [20] is used to map test points onto embedded feature space. To get the best recognition performance, dimension of embedded space varies 5 to 30; the neighbors number changes 5 to 40. Both LLE and LPP codes are acquired from the web [21].

It is a little surprise to notice that the identification performances of them are much worse than B-Spline construction technique although LLE and LPP are "learning" techniques. The reason may partly be that most manifold learning methods depend on data set good normalization and alignment, whereas the data set is not normalized well and contain much noise (although sampling device made ear images to be coarsely normalized). Conversely, this also shows the efficiency of our method. In addition, supervised LPP (equivalent to LDA) will get better results than LLE and unsupervised LPP, this is because supervised learning is able to acquire better separability than unsupervised learning. In general, for multi-view ear recognition, this contrast shows that the performance of explicitly constructing B-Spline pose manifold is better than that of manifold learning from training samples.

V. CONCLUSIONS

In this work, multi-view ear recognition across large pose methods beyond existing works in 2D ear biometrics is investigated. And NKDA is utilized to extract multi-view ear non-linear features and construct ear pose manifolds by B-Spline interpolation in discriminative feature space. Our system reports a 97.7% rank-one recognition rate against large pose variations in our multi-view ear data set. Interpolation test shows the method of B-Spline pose manifold explicit construction is better than implicit manifold learning methods and traditional statistical analysis methods.

Experiments show that our method can solve the multi-view ear recognition problem efficiently. Since multi-view ear detection is an important pre-processing step of ear recognition, in the future, attention will be paid on it. In addition, the extrapolation experiments will be further tested to validate our multi-view ear recognition method.

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