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Surveillance Mining System for Low Resolution Face Image Recognition Using Kernel Coupling

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ABSTRACT— Video surveillance systems for face recognition are confronted with low-resolution face images. Low resolution face images coming from real time video does not give discriminant information to identify similar images in a dataset. Traditional method solved this problem through employing super- resolution (SR). But these are time-consuming, sophisticated SR algorithms. These algorithm are not suitable for real-time applications. To avoid the limitations, in this work, new feature extraction method for LR faces called coupled kernel distance metric learning (KCDML) is proposed without any SR pre-processing. By using a kernel trick and a specialized locality preserving criterion, we formulated the problem of coupled kernel embedding as an optimization problem whose aims are to search for the pair-wise sample staying as close as possible and to preserve the local structure intrinsic data geometry. Instead of an iterative solution, one single generalized Eigen- decomposition can be leveraged to compute the two transformation matrices for two classifications of data sets.

KEYWORDS— Face recognition, low-resolution, feature extraction, kernel, super-resolution.

I. Introduction

The performance of a real-world face recognition system usually declines when the input face images are low-resolution (LR) with size of only 12 ×12 pixels. This is a critical problem for surveillance circumstances. Compared with high-resolution (HR) images, these LR images lose some discriminative details across different persons. Intuitively, recovering the lost information of LR face images first is a promising solution for achieving better performance. A Fig.1 shows the problem of LR face recognition where it is very difficult to find similarity between these images. In fact, most existing "two-step" methods of LR face recognition employ a pre-processing of SR as the first step. Subsequently, the super-resolved face images are passed to the second step for recognition. During the past decade, many.

SR methods are proposed to predict the corresponding HR image from a single LR image [4] or multiple LR ones [3].

Figure 1. Problem for LR face recognition.

Baker and Kanade [5] propose "face hallucination" to infer the HR face image from an input LR one based on face priors. To overcome the drawbacks of previous methods, we propose a new efficient method for LR face recognition without any Super Resolution preprocessing. According to the aim of recognition, we learn the coupled projections to map the images with different resolutions into a unified feature space and carry out the recognition in the new space. A suitable distance function is significant for many real-world applications involving high-dimensional data (such as image annotation [7], image retrieval [8], image segmentation [9] and many others.

Euclidean distance is widely used for similarity measure but because of variation in the dimension of LR and HR images above assumption will not make valid. To solve this problem employ super resolution function to project the LR image into the target HR space.

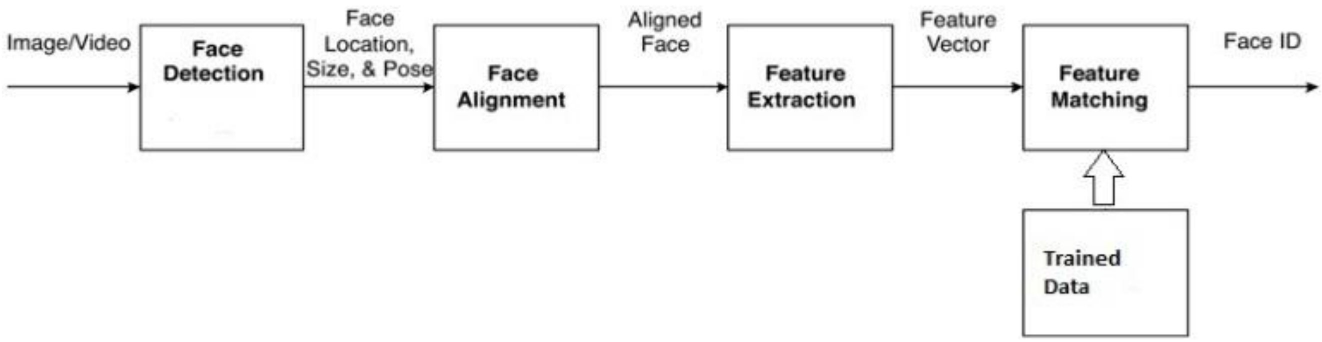

Figure 2. Model for Face Recognition

II. RELATED WORK

Euclidean distances are replaced with so-called Mahalanobis distances. It works with various linear and nonlinear methods; such as principal component analysis (PCA), locality preserving projection (LPP) [10] but a Mahalanobis distance metric also may encounter problems in performance due to the estimation of so many parameters. Generally the metric learning is accomplished based on the pair-wise constraints among training samples, if the number of training samples is large enough then its performance will be great. Otherwise it degrades [11].

Lower dimensional representations are more useful for visualizing high-dimensional data, the obtained sub-manifold is tuned to the training data and due to noise, cropping, distortion, and even samples artificially captured from multiple camera views new data points will likely lie outside the sub manifold. Therefore, it is necessary to specify someway of projecting the off-manifold points into the manifold via metric learning. Therefore, the proposed approach is not applicable to nonlinear situations. In addition, its performance depends fundamentally on the distribution of nonlinear pattern. This paper largely extends [12] by proposing a new kernel coupled distance metric learning approach for face recognition, as recognition performances of inconsistent matching issues such as matching between face images of various resolutions and even between face images with various resolutions and different poses.

III. KERNEL COUPLED DISTANCE METRIC LEARNING

Metric learning is similarity measures between various shapes such as curves, surfaces etc. In this paper we use Gaussian kernel function for metric learning between two different set of images. After that we use kernel distance metric criteria to create objective function and then it transfer to generalize Eigen decomposition problem in nonlinear space. Finally we use nearest neighbor classifier as classification tool.

Suppose we have two sets of images $\mathbf{X_1}$, $\mathbf{X_2}$, $\mathbf{X_3},\ldots,\mathbf{X_M}$, and $\mathbf{Y_1}$, $\mathbf{Y_2}$, $\mathbf{Y_3}\ldots$ $\mathbf{Y_M}$ Each image matrix is converted into vector before metric learning such $\mathbf{x_1}$, $\mathbf{x_2}$, $\mathbf{x_3}$,……, $\mathbf{x_M}$ and $\mathbf{y_1},\mathbf{y_2},\mathbf{y_3},\ldots\mathbf{y_M}$ respectively. Let Φ be nonlinear mapping. Above vectors are mapped to higher dimension space using a map in feature space (F) $\phi.R^M \rightarrow F$, that is $\phi(x_1)$, $\phi(x_2)$, $\phi(x_3)$,…..,$\phi(x_M)$ and $\phi(\mathbf{y_1})$, $\phi(\mathbf{y_2})$, $\phi(\mathbf{y_3})$,…..,$\phi(\mathbf{y_M})$[6].

Algorithm:

The algorithm procedure is given below.

Step 1: All images are converted into vector and then realign as X=[$\mathbf{x_1,x_2,x_3,\ldots,x_M}$] and Y=[$\mathbf{y_1,y_2,y_3,\ldots,y_M}$] for different kind of data.

Step 2: X and Y are recalculated in the terms of Dot Product as K_x and K_y given below.

$$K_x=\begin{bmatrix} <\phi(x_1),\phi(x_1)> & <\phi(x_1),\phi(x_2)> & \cdots & <\phi(x_1),\phi(x_M)> \\ <\phi(x_2),\phi(x_1)> & <\phi(x_2),\phi(x_2)> & \cdots & <\phi(x_2),\phi(x_M)> \\ \vdots & \vdots & \ddots & \vdots \\ <\phi(x_M),\phi(x_1)> & <\phi(x_M),\phi(x_2)> & \cdots & <\phi(x_M),\phi(x_M)> \end{bmatrix} \quad (1)$$

$$K_y=\begin{bmatrix} <\phi(y_1),\phi(y_1)> & <\phi(y_1),\phi(y_2)> & \cdots & <\phi(y_1),\phi(y_M)> \\ <\phi(y_2),\phi(y_1)> & <\phi(y_2),\phi(y_2)> & \cdots & <\phi(y_2),\phi(y_M)> \\ \vdots & \vdots & \ddots & \vdots \\ <\phi(y_M),\phi(y_1)> & <\phi(y_M),\phi(y_2)> & \cdots & <\phi(y_M),\phi(y_M)> \end{bmatrix} \quad (2)$$

Each term in the K_x and K_y are calculated by Gaussian Kernel function which implicitly calculate the dot product of x_i and y_j in higher dimension space [6].

$$K_x(i,j)=\exp\left(-\frac{\|x_i-x_j\|^2}{2\sigma^2}\right) \quad (3)$$

$$K_y(i,j)=\exp\left(-\frac{\|y_i-y_j\|^2}{2\sigma^2}\right) \quad (4)$$

Sometimes real world data do not satisfy $\sum_{i=1}^{M}\phi(x_i)=0$ or $\sum_{i=1}^{M}\phi(y_i)=0$ so $K_x$and K_y are replaced by

$$\tilde{K}_x=K_x - 1_M K_x - K_x 1_M + 1_M K_x 1_M \quad (5)$$

$$\tilde{K}_y = K_y - 1_M K_y - K_y 1_M - 1_M K_x 1_M \quad (6)$$

Figure 3. Face images for one individual

Step 3: Solve the generalize Eigen decomposition problem and apply regularization ($r=10^{-7}$). $(\boldsymbol{ZZ^T}=\boldsymbol{ZZ^T}+rI)$

$$(Z\theta Z^T)\,W = \lambda\,(ZZ^T)W \tag{7}$$

$$\text{Where } W=\begin{bmatrix}\alpha\\ \beta\end{bmatrix},\ Z=\begin{bmatrix}Kx & \\ & Ky\end{bmatrix},\ \theta=\begin{bmatrix}I & -I\\ -I & I\end{bmatrix}$$

W composed of smallest Eigen vector in which $\alpha \epsilon R^{M*d}$ corresponds to the 1st to Mth rows of matrix W and $\beta \epsilon R^{M*d}$ corresponds to the $(M+1)^{th}$ to 2Mth rows of Matrix W.

Step 4: X and Y are coupled into the same unified kernel space

$$F_{x}= \alpha^T \tilde{K}_x \tag{8}$$
$$F_{y}= \beta^T \tilde{K}_y \tag{9}$$

Where $F_{x}=[f_{x1}, f_{x2}, \dots, f_{xM}]$, $F_{y}=[f_{y1}, f_{y2}, \dots, f_{yM}]$ whose entries $f_{xi}\,(i = 1, \dots, M)$ and $f_{yj}\,(j = 1, \dots, M)$ corresponds to features of $\mathbf{x_i}$ and $\mathbf{x_j}$.

Step 5: Testing image coming from video is realign into single vector recorded as $\acute{y}$ and mapped into $(\acute{y})$ in higher dimension space. The kernel coupled feature $f_{\acute{y}}$ for this sample derived as follows:

$$\acute{f}_y = \beta^T \bar{K}_y \tag{10}$$

Where $\bar{K}_y$ which is centralize form of $\acute{K}_y = [\phi(y_1).\phi(\acute{y}), \phi(y_2).\phi(\acute{y}), \dots, \phi(y_M).\phi(\acute{y})]^T$ can be computed as follows

$$\bar{K}_y = \acute{K}_y - K_y 1^T{}_{1\times M} - 1_M \acute{K}_y + 1_M K_y 1^T{}_M \tag{11}$$

Where $1_{1\times M}$ is 1×M unit matrix whose coefficient is 1/M. After feature extraction, nearest neighbor Classifier is used to predict class of incoming image as

$$D(f_{xc}, \acute{f}_y) = \text{argmin}\, D(f_{xj}, \acute{f}_y) \tag{12}$$

i.e. $\acute{f}_y$ is closest to f_{xc}, therefore it belongs to the class of fxc.

IV. EXPERIMENTS

A set of experiments carried out on benchmark database i.e. UMIST face database [13] to evaluate the performance of proposed algorithm. UMIST face database consist of 564 images of 20 individuals with different views. In experiment, the training samples were randomly selected, the remaining was for testing, and the nearest neighbor classifier was used for classification. The experiments for a certain case were repeated 30 times, and the recognition precision is obtained as the average of the ratio of the number of correctly classified test samples out of the total test samples.

KCDML is employed on variant face poses and different resolutions using UMIST face database. Fig. 2. Shows that nine samples with the original size of 12×92pixels for each individual with different orientation are used. The first, middle and last three are labelled as lateral, oblique and frontal faces with the short-name 'lf', 'of' and 'ff' respectively.

KCDML needs more vector feature points to make face images under variant poses more consistent. The Correct Classification Rates(CCR) achieved by CDML[14], PCA-RBF[15], Kernel-PCA(KPCA), LPP and KLPP[16] are 0.6, 0.3, 0.6, 0.375, 0.75 respectively all with 18D features, while for PCA, the recognition rate with 14D features is 0.3[6].

Table 1 Comparison of recent algorithm for face recognition

Sample set	Training Testing	ff ff lf lf	ff ff of of	lf lf of of	lf lf ff ff	of of ff ff	of of lf lf
KCDML		**0.875**	**1**	**1**	**0.925**	**0.9**	**0.925**
CDML		0.6	0.925	0.875	0.625	0.625	0.525
PCA-RBF		0.3	0.625	0.7	0.475	0.425	0.575
PCA		0.3	0.775	0.35	0.175	0.5	0.775
KPCA		0.6	0.95	0.9	0.7	0.75	0.625
LPP		0.375	0.85	0.275	0.125	0.375	0.8
KLPP		0.75	1	0.975	0.85	0.85	0.7

CCRs of KCDML was calculated with value of $\boldsymbol{\sigma}$ being 1500 with 'ff' and 'lf'. Value of $\boldsymbol{\sigma}$ is depends upon images orientation and resolutions. In some paper, Gaussian kernel parameter set as $\boldsymbol{\sigma} = \sum_{i,j}\|\mathbf{x_i}-\mathbf{x_j}\|^2/N^2$,where N is number of training images. Three kinds of experiment tests were designed: lateral, oblique and frontal face recognition under different resolutions such as 28*24, 12*10 and 8*6 pixels respectively, as shown in Fig. 3 Especially, the facial orientation of all samples in register set and test set are the same, but with different resolutions.

112*92 28*24 12*10 8*6 6*4

Figure 4. Different resolutions for one individual

Impact of face images with different resolutions and poses were tested with six kind of experiment. Each experiment of one paired samples, namely frontal face coupled with lateral face, frontal face coupled with oblique face, lateral face coupled with oblique face, lateral face coupled with frontal face, oblique face coupled with frontal face, and oblique face coupled with lateral face for each individual was conducted.

V. CONCLUSION

This work presents an approach to solve a problem of LR face recognition. Proposed algorithm projects the face images with different resolutions and poses into a unified feature space through kernel coupled distance metric learning. This time saving method, without any SR, is more suitable for real-time applications.

Key point of KCDML is that it transform the input data into a higher-dimensional feature space, which leads to a reduction in the small sample size problem occurring in conventional supervised learning algorithms and the decoupling procedure of KCDML can be solved by a generalized Eigen-decomposition problem. Performance of KCDML is very high as compare to the CDML, PCA-RBF, KPCA, LPP, and KLPP. So KCDML is well suited method for real time face recognition in video surveillance system.

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