Face Image Super-Resolution Using Two-dimensional Locality Preserving Projection

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Abstract

Super-resolution is an important method to reconstruct high-resolution images from low-resolution images. In this paper, a manifold learning algorithm based on two-dimensional locality preserving projection (2D-LPP) is proposed for face image super-resolution. The 2D-LPP detects the intrinsic manifold structure of high space and preserves the structure in low space by projection. The projection approach in the 2D-LPP resolves the out-of-sample problem in embedding-based manifold learning methods, and improves the speed in reducing the dimension of a new sample data. Moreover, the 2D-LPP preserves more accurate manifold structure by directly operating on 2D images rather than flattened 1D vector as PCA and LPP does. Extensive experiments are conducted on the AR and FERET databases. Experimental results show that the proposed method performs better than PCA based super-resolution in both PSNR and time efficiency.

1. Introduction

The super-resolution research has been considered as a critical image reconstruction method in many applications [1], such as medical imaging, HDTV, image-based rendering, face recognition, and video surveillance. The goal of super-resolution is to improve the spatial resolution of source images which have low resolution. The resolution enhancement is especially useful for face recognition in biometrics and surveillance [2].

However, the super-resolution problem is challenging due to that it is ill-posed [3]. Therefore an observation model describing the degradation process of imaging is assumed. An optimization approach can then be applied to super-resolve the low-resolution source images. There are four kinds of super-resolution methods to obtain high-resolution images: interpolation-based, reconstruction-based, learning-based, and dimension reduction-based methods.

Interpolation-based methods such as nearest neighbor, bilinear, and bicubic interpolation are intuitive solutions. They use uniform kernel functions to resize images by neighbor pixels. Clark et al. [4] proposed a nonuniform interpolation approach which includes three steps: registration, interpolation, and deburring. Interpolation-based methods are available only when all source images have the same degradation process.

Reconstruction-based methods reconstruct global images. Stack and Oskoui [5] adopted the projection-onto-convex-sets approach which has been used in image enhancement. It is an iterative approach to reduce the blocking effect of reconstructed images. Irani and Peleg [6] described an iterative back-projection (IBP) approach. They used the difference between observation images to predict high-resolution images. Reconstruction-based methods have the problem of high computational complexity.

Learning-based methods employ training algorithms to reconstruct a clear image from observation images. Tipping and Bishop [7] adopted Bayesian to solve super-resolution problems. Kanemura et al. [8] describes an additional layer of edge with markov random fields to reconstruct images. Learning-based methods also have the problems of high computational burden.


In this paper, we propose a two-dimensional locality preserving projection (2D-LPP) [12] method for super-resolution. 2D-LPP is one of dimensionality reduction methods that can reduce high-resolution images to features but preserve their locality information by nearest neighbors. 2D-LPP is based on LPP but preserves locality information in both directions of images for increasing computational efficiency. The method can predict features...
to reconstruct high-resolution images with higher computational efficiency. The 2D-LPP super-resolution could reconstruct super-resolution images which are similar as truth images from local training images.

2. The Framework of Dimension Reduction-Based Super-resolution

Dimension reduction-based super-resolution methods can super-resolve low-resolution images. An observation model is defined for the degradation from a high-resolution image to a low-resolution image. Some of super-resolution methods inverse the observation model to reconstruct the high-resolution images from the low-resolution image. Dimension reduction methods can transform a high-resolution image to a high-resolution feature for locality information. Dimensionality reduction-based super-resolution methods rely on the observation model to build the relationship between the high-resolution feature and the low-resolution image. Thus, a super-resolution image can be reconstructed from the high-resolution feature which comes from the low-resolution image.

A digital image suffers from blur and noise caused by sensors and transmission. Real world images which are caught by sensor have some natural loss by optical distortions, motion blur, and sensor noise. The relationship of high-resolution images and low-resolution images in high-dimensions can be formulated as an observation model:

$$ Y_i = MX_i + n, $$  

(1)

where $X_i$ is a high-resolution image, $Y_i$ is a low-resolution image, $M$ is down sampling matrix, and $n$ is noise.

Dimension expansion methods which come from dimension reduction can obtain super-resolution images by the observation model. When a high-resolution feature $x_i$ is obtained, a high-resolution image $X_i$ can be received as:

$$ X_i = V^+ x_i, $$  

(2)

where $V^+$ is an expansion matrix. By combining Eq.(1) with Eq.(2), we can get a new transform formula between the high-resolution feature and the low-resolution image:

$$ Y_i = MV^+ x_i + n. $$  

(3)

Combining ML estimator with Eq.(3) as:

$$ \tilde{x}_i = \arg \min_{x_i} \| MV^+ x_i - Y_i \|^2, $$  

(4)

which minimizes as:

$$ \tilde{x}_i = (V^+)^T M^T M V^+ x_i. $$  

(5)

The expansion matrix $V^+$ is calculated from training data by dimension reduction methods. It can let high-resolution feature map to high-resolution image. The main idea is that the high-resolution feature which preserves most of variance is far less than high-resolution image.

3. 2D Locality Preserving Projections for Super-resolution

2D-LPP [12] which is based on LPP can preserve most of variance to reconstruct super-resolution images on 2D images. The proposed 2D-LPP super-resolution method includes a learning process and a dimension expansion process. A projection matrix $V$ is calculated from high-resolution images by 2D-LPP in learning process. Then the dimension expansion process super-resolves low-resolution images by using $V^+$.

3.1. Learning the super-resolution manifold by 2D-LPP

The main goal is to get a projection matrix $V$ by 2D-LPP. 2D-LPP uses the relationship of training data to construct a weight matrix. Solving generalized eigenvalue problems can calculate the projection matrix $V$ by the weight matrix.

Let face images $X_i, 1 \leq i \leq N$, be $m \times n$-dimension images. Project high-resolution images $X_i$ to high-resolution feature $x_i$ by the projection matrix $V$:

$$ x_i = X_i V. $$  

(6)

Using 2D-LPP can get the projection matrix $V$ by high-resolution images $X_i$. The algorithm includes 3 steps:

1. Building a nearest neighbor graph : Let $W$ be a graph with $N$ nodes which represent the $N$ face images $X_i$. If $X_i$ and $X_j$ are close, put an edge between nodes $i$ and $j$ in $W$ by $k$-nearest neighbors. The $k$ nearest neighbor nodes of nodes $i$ are found by using Euclidean distance.

2. Setting up the weight : Let $S$ be a $N \times N$ symmetric matrix. $S_{ij} = 0$ if there is no edge between nodes $i$ and $j$, otherwise $S_{ij}$ can be set by the heat kernel defined as follows:

$$ S_{ij} = e^{-\frac{\| x_i - x_j \|^2}{t}}, $$  

(7)

where $t$ is a diffusion parameter of the heat kernel.
3. Constructing the projection matrix \( V \): If \( X_i \) and \( X_j \) are close, \( x_i \) and \( x_j \) are close either. Thus, the projection matrix \( V \) can be defined by

\[
\min \sum_y \| y_i - y_j \|_2^2 S_{ij}.
\] (8)

According to Eq.(6), Eq.(8) can be minimized as follows,

\[
\sum_y \| y_i - y_j \|_2^2 S_{ij} = \sum_y (X_i^T X_j - X_j^T X_i) S_{ij} = V^T \left[ \sum_j X_j^T \sum_i S_{ij} - \sum_i X_i^T S_i X_i \right] V
\]

\[
= V^T \left[ X_i^T (D - S) X_i V \right] V
\]

\[
= V^T X_i^T (D - S) X_i V = V^T L_X V,
\] (9)

where \( D \) is a diagonal matrix, \( D = \sum_y S_{ij} \), and \( L = D - S \) is called the Laplacian matrix. \( L \) and \( D \) are both \( N \times N \) matrix. Set a constraint as follows:

\[
V^T X_i^T DXV = 1.
\] (10)

Thus, the minimization can be found as:

\[
\min V^T X_i^T DXV.
\] (11)

The projection matrix \( V \) can be calculated by solving the generalized eigenvalue problem:

\[
X_i^T DXV = \lambda X_i^T DXV.
\] (12)

Take the eigenvectors \( v_0, v_1, ..., v_D \) corresponding to the eigenvalues, \( \lambda_1 < \lambda_2 < ... < \lambda_D \) which are the \( D \) smallest eigenvalues. Combine with Eq.(6) as:

\[
x_i = X_i V, \quad V = (v_0, v_1, ..., v_D), \quad i = 1 - N,
\] (13)

where \( x_i \) is the feature of the high-resolution image \( X_i \), and \( V \) is the projection matrix.

### 3.2. Dimension expansion by 2D-LPP

A low-resolution image can be reconstructed to a high-resolution image by a dimension expansion process. Images can be modeled as \( x_i = X_i V \) in Eq.(6) by using 2D-LPP method. Thus, the function can be changed as:

\[
X_i = s_i V^+,
\] (14)

where \( V^+ \) is called an expansion matrix from \( V^+ = V^T (V V^T)^{-1} \). The observation model of high-resolution images and low-resolution images has to be changed by Eq.(1):

\[
Y_i = M_s X_i M_w + n,
\] (15)

where \( X_i \) is a high-resolution image, \( Y_i \) is a low-resolution image, \( M_s \) and \( M_w \) are down sampling matrices of height and width, and \( n \) is noise.

By combining Eq.(15) with Eq.(14), the function of a low-resolution image \( Y_i \) which can be calculated by a high-resolution feature \( x_i \) is shown as:

\[
Y_i = M_s x_i V^+ M_w + n.
\] (16)

We modify Eq.(16) in order to combine with ML estimator as:

\[
\hat{x}_i = \arg\min_{x_i} \| M_s \hat{x}_i V^+ M_w - Y_i \|^2.
\] (17)

When a high-resolution feature \( \hat{x}_i \) is calculated, a predictive high-resolution image \( \hat{X}_i \) can be obtained by:

\[
\hat{X}_i = \hat{x}_i V^+.
\] (18)

### 4. Experimental Results

The experiments are carried on the FERET database and the AR database. The images are frontal face images without occlusion. 298 FERET images, 178 men and 120 women, and 57 AR images, 23 men and 34 women, are used. The resolution of images is normalized to 140×100 pixels. 710 high-resolution images are obtained by flipping the FERET and AR source images horizontally. Fig.1 shows some example images.

![Experimental face images.](image)

We chose one nearest neighbor, \( k=1 \) and Gaussian blur with \( 5 \times 5 \) mask for the training of 2D-LPP. In super-resolution experiments, we will change cumulative percentage of variance to see effects of super-resolution images. We count PSNR (Peak Signal to Noise Ratio) which is calculated from the difference between super-resolution and ground truth images.

Performance comparison between our method and linear PCA is achieved by changing cumulative percentage of variance from 0.70 to 1.00. We take 700 images for training and 10 images for test. The PSNR results are shown in Fig.2. Our method has better PSNR than that of linear PCA for all variance conditions, because our 2D-LPP method can maintain the manifold structure of data. Fig.3 shows super-resolved images by our method and linear PCA. The linear PCA method has ghost effect around eyes,
nose, and mouth. Moreover, it lets in some noise when variance is too much. Our method has good performance around face contour and margin but has block effect.

![Fig. 2. PSNR of changing cumulative percentage of variance.](image)

(a) (b) (c) (d) (e)  
![Fig. 3. Super-resolution images](image)  
(a) Ground truth  
(b)-(c) Our method changes variance: 0.95, 0.99  
(d)-(e) Linear PCA changes variance: 0.95, 0.99.

The test time of our method and linear PCA is shown in Fig. 4. Our method takes less time than linear PCA when variance rises, because the dimension of the expansion matrix $V$ of our method, $n \times n$, is smaller than that of linear, $700 \times 14000$, ie., $N \times mn$.

![Fig. 4. Test time of changing cumulative percentage of variance.](image)

5. Conclusion

A super-resolution method which combines 2D-LPP with ML estimator is proposed in this paper. The 2D-LPP detects and preserves the intrinsic manifold structure from high space to low by projection. We calculate an expansion matrix by 2D-LPP from high-resolution images. A super-resolution image can be obtained from a low-resolution image by the expansion matrix and ML estimator. The experimental results show that our method performs better than linear PCA. When training number or variance increasing, the testing time of our method is not increasing too much.

The future task would be toward getting greater super-resolution images. This can be achieved by extending 2D-LPP to two-directional 2D-LPP which can preserve manifold in both row and column directions. MAP estimator can be adopted for better performance.

References


