Comparison of Multimodal Low Resolution Face Recognition using SVD and DSR Methods.

ROSHNA N. R.
Dept. of Electronics and communication engineering
LBS Institute of Technology for Women Poojappura
Trivandrum, India
roshnanr91@gmail.com

NAVEEN S.
Dept. of Electronics and communication engineering
LBS Institute of Technology for Women Poojappura
Trivandrum, India
nsnair11176@gmail.com

ABSTRACT— Face recognition is effective when input test images are of high resolution (HR). But face images captured by surveillance cameras are of low resolution (LR) uncontrolled pose and illumination etc. The main objective of this paper is to compare two methods, which provide better recognition accuracy for more number of test images. The methods are Singular Value Decomposition (SVD) method and Discriminative Super-resolution(DSR) method. First, set a LR and HR face images as reference images of each subject. Then find the minimum error between LR test image and LR reference images using Principle Component Analysis (PCA).To find the error between LR test image and HR reference images, first reconstruct the test image into a HR image. In-order to reconstruct HR image from test image Singular value decomposition (SVD) and Discriminative Super-resolution methods are needed. Then compare the recognition accuracy of both methods individually. The entire algorithms are experimentally done for both texture and depth images.

Keywords-Bicubicinterpolation;SVD,DSR,PCA.

I. INTRODUCTION

Face recognition has always been a very challenging task for the researches. It presents a challenging problem in the field of image analysis and computer vision. The security of information is becoming very significant and difficult. There are various biometric authentication techniques for human recognition, they are figure print recognition, speech recognition, iris recognition, signature recognition, etc. These recognition techniques differ from face recognition because they require the active participation of persons. So face recognition is more advantageous compared to other biometrics.With the growing installation of surveillance cameras in public areas, ranging from a small scale stand-alone camera application in banks and supermarkets to a large-scale multiple networked CCTV in large enforcement application in Public Street, there is an increase in demand of face recognition technology. Wide angle cameras are normally used and installed in a way that the viewing area is maximized. But the face region in the scene is normally very small. When the person is not close to the camera, face region will occupy less than a hundred of pixels. Recognition of such a very low resolution face images can be done by several methods. Among those methods which will provide better accuracy is a challenging task. Here, two methods are proposed to find the error and the recognition accuracy of both texture and depth images. PCA is used to find the weighting coefficients of test images and reference images. The mean square error (MSE) between LR test images and LR reference images can be calculated directly. But in the case of LR test image and HR reference images, it is not possible because of its dimensionality problem. Inorder to overcome this problem two methods are used to

reconstruct the HR image from test image. SVD method is used to decompose the image into singular values without changing their dimensionality. Then bicubic interpolation method is used to interpolate the LR image. After this inverse SVD is done and find the weighting coefficients of both reconstructed HR and HR reference images. Then find the recognition accuracy. Similarly DSR method is used to find the relationship operator (R).The reconstructed HR image is obtained by multiplying R with low-resolution test image. Then find the weighting coefficients using PCA and find the recognition accuracy. R can be find mathematically using least square solution method. The entire process is done for both texture and depth images.

Fig 1.High Resolution Texture image

Fig 2.High Resolution depth image

In image processing research field, reconstruction of an HR image from LR input is commonly called super-resolution. For face images, it is called face hallucination[1].Super-resolution (SR) techniques are mainly classified as Interpolation based SR, Reconstruction based super-resolution, and Example based SR. Reconstruction based SR method assumes that the observed LR image could be represented as a degraded HR image. This method is mainly divided into two, Iteration back projection and Regularization method. The advantage of Iterative back projection is to remove the noise and blurring effect from the image. But the disadvantage is that it has no unique solution. Advantage of regularization method is that there is no need of large training dataset, the preservation of image details is high. Example based SR method includes Learning based SR method, Regression method, Sparse coding method. The disadvantage of learning based method is One- to-multiple mapping of LR patch to HR patch results in image quality degradation. Regression method is computationally faster ,but it is expanded in the whole set of training data points and accordingly computational demanding occurs both in training and in testing. The sparse coding technique fails to consider the incoherence of dictionary entries, when consider the geometrical structure of data. Here, in the proposed method Interpolation based SR method is used. This method tries to recover the missing information from neighboring pixels. It is quite straight forward, but the quality is not tolerated when the scale factor is getting larger. The major disadvantages of both nearest neighboring and bilinear interpolation are that it does not have sub pixel accuracy and it creates the artifacts. Bicubic interpolation method is the most popular and basic method used in SR methods, It provides better smoothness and fast computation. Among these methods the bicubic Interpolation is better SR method and it is used in this paper. Inorder to measure the mean square error between the LR test image and HR reference image, we must ensure that they are of the same size. To make the test and the reference image in same size the bicubic interpolation method is necessary for test images. This method makes the test image at the same size as that of the reference image.

II. PROPOSED METHODOLOGY

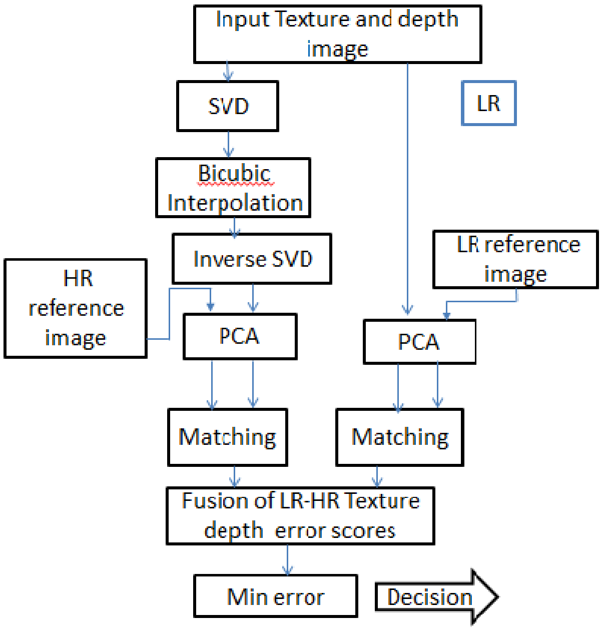

Fig3.Flow chart of entire algorithm for SVD Texture and Depth

Here the above figure shows the chart of entire algorithm using SVD method.We have a set of LR and HR images in the databse.First we set a reference image from both LR and HR datasets.Inorder to find the meansquare error,take the difference between weighting coefficients of inputLR with weighting coefficients of LR refernce images.To match input LR test image with HR reference imagefirst convert LR input image intc corresponding singular values using SVD. SVD is mainly used to decompose the image based on their singular values, without making any variations in the image dimension.

$$A=UW\check{V} \quad (1)$$

Then use the bicubic interpolation method to interpolate the input image and take take the inverse SVD also.Thus we get the reconstructed HR image.Next step is to match this reconstructed HR image with HR reference image.The entire step is done for both Texture and depth images.Then find the recognition acuracy of both methods individually.The experimental results of above method is shown in the next section.

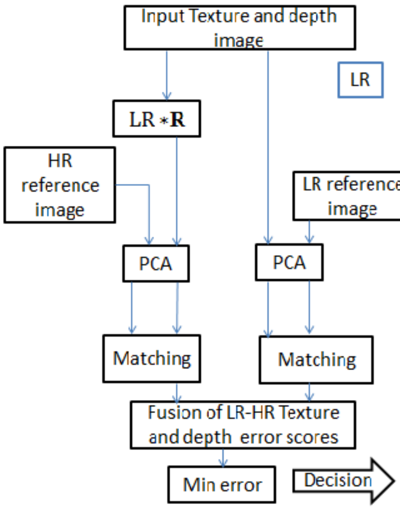

Fig4.Flow chart of entire algorithm for DSR Texture and Depth

Here in this method matching between LR reference image and input LR test image can done directly. But in the case of matching between LR test image and HR reference image reconstruction procedure is needed. Here for reconstruction of HR image, first find the relationship operator between LR and HR image space. Then multiply input LR image with the relationship operator R.Thus we get the reconstructed HR image. R is obtained mathematically by using lest square solution equation.

$$R' = [\sum_{i=1}^{N} (I_h^{\;i} I_l^{\;i})][\sum_{i=1}^{N} (I_l^{\;i} I_l^{\;i})]^{-1} \quad (2)$$

$$R = \arg\min_{R'} \sum_{i=1}^{N} ||I_h^i - R' I_l^i||^2 \quad (3)$$

$$I_h = R I_l \quad (4)$$

Here I_h represent reconstructed HR image, I_l represent input LR image.

A. Principle component analysis(PCA)

Use of spectral transformation will make the data samples almost uncorrelated. Even then, Some spatial dependency may exist. So PCA is used for the correlation process as it uses orthogonal transformation to get linear uncorrelated ata sets called principal components. Conventional covariance method for the calculation of principal components is used here. Feature extraction using 1D-PCA is done as follows.

Let Xi be the spectral tansformed1D Euclidean metric which represents ith person, it is grouped as a MxN matrix X=[X1 X2 X3..XN],where N is the number of face samples under consideration.

Mean vector is calculated as follows,

$$X_m = \frac{1}{N} \sum_{i=1}^{N} X_i \quad (5)$$

Standard deviation will be calculated as,

$$X_{SD} = \frac{1}{N} \sum_{i=1}^{N} (X_i - X_m) \quad (6)$$

Covariance matrix is calculated as,

$$X_{COV} = X_{SD} * X^T_{SD} \quad (7)$$

This is a matrix of size MxM, which is of very large dimension. Also it gives M eigen values and M Eigen vectors which are very large in number to process. The base idea of dimensional reduction by changing the construction of covariance matrix can be now used.

$$X_{COV} = X^T_{SD} * X_{SD} \quad (8)$$

The result is a matrix of size N x N, where N is the number of subjects under consideration. It gives N Eigen values and N Eigen vectors. The Eigen values are sorted in descending order and will select the first N' largest Eigen values and corresponding Eigen vectors. Eigen vectors in N' dimension is transformed to the higher dimension of M by multiplying with Standard deviation Matrix. Now the test data is projected to this lower dimension space to get the corresponding weight vectors. In 2D-PCA 2D spectral representation of Depth map is considered. The only difference in calculating the Covariance matrix is that here a 2D matrix is used when compared to 1D Matrix in 1D-PCA. After determining the Eigen values and Eigen vectors a 2D weight vector matrix is obtained which is then converted to a column matrix.

III. RESULTS AND COMPARISON

For analysis and testing FRAV3D database is used here.FRAV3D consist of HR images only. Here in this paper the test image is LR. So inorder to get the low resolution test images, first down sample the entire database with a magnification factor of 4.In this experiment mainly 80 samples of 10 different subjects are used. The recognition accuracy is experimentally find for texture alone and its combined accuracy. The values are tabulated below. Here the table1 shows accuracy of texture. In table 1.maximum low resolution and high resolution accuracy is obtained for 16 numbers of samples. When number of samples increases the recognition accuracy of both LR and HR images decreases. This will also show that as the number of samples increases the recognition accuracy decreases. But compared to other algorithms these accuracies are not very bad. When analyzing the tables, as the number of samples increases the accuracy decreases by a small rate.

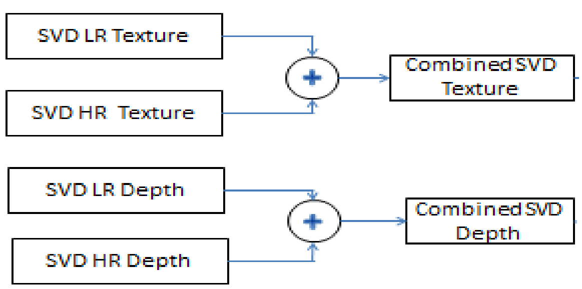

Fig5.Combined SVD Texture and Depth image

TABLE 1.Using Texture and Depth images using SVD

Num of samples	Low Texture	High Texture	Combined Texture	Low Depth	High Depth	Combined Depth
80	76.25	36.25	**85**	58.75	45	**60**
160	71.25	41.87	**71.87**	49.37	35.62	**49.37**
240	61.25	30	**60.83**	45	29.58	**45.83**
320	60.93	33.43	**60**	43.75	24.06	**44.06**
400	60.5	32.25	**58.5**	42.25	25.25	**42.5**
480	57.29	30.41	**56.66**	40.62	23.12	**40**
560	55.89	28.75	**54.64**	39.10	22.67	**39.64**
640	56.25	23.90	**56.09**	39.53	21.56	**39.21**
720	54.72	20.97	**54.30**	39.02	21.11	**39.44**
800	55.375	26.75	**53.625**	39.25	22.5	**39.3**
1000	47.1	23	**45.4**	32.5	18.7	**32.6**
1600	43.43	21.62	**42.25**	34.3125	17.93	**34.5**

Here from the above table it shows that as number of samples increases the recognition accuracy value decreases but number of recognition of correct images increases gradually. For 560 samples 350 images are correct for texture and 250 images are correct for depth images. For 1600 samples 720 images are correctly recognized for texture and 620 are recognized for depth.

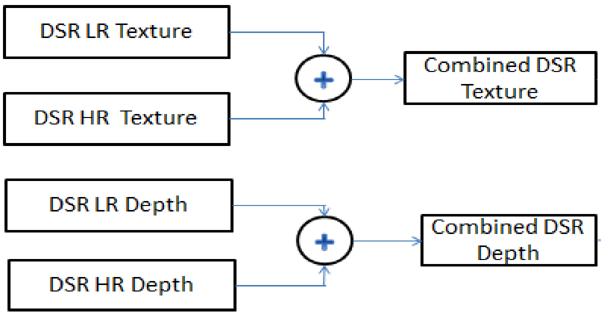

Fig6.Combined DSR Texture and Depth image

TABLE 1.Using Texture and Depth images using DSR

Num of samples	Low Texture	High Texture	**Combined Texture**	Low Depth	High Depth	**Combined Depth**
80	76.25	43.75	**78.75**	60	17.5	**62.5**
160	71.25	48.12	**70.625**	48.75	6.25	**49.375**
240	61.25	39.58	**61.25**	45	8.33	**44.58**
320	60.93	39.06	**61.25**	43.75	6.25	**44.37**
400	60.5	33	**60.25**	41.75	4.25	**43**
480	57.29	32.5	**57.29**	40.41	3.54	**41.25**
560	55.89	31.07	**56.25**	39.28	3.21	**40.17**
640	56.09	31.40	**55.46**	39.68	3.12	**39.37**
720	54.86	29.16	**54.44**	39.16	2.5	**39.16**
800	55.37	31.12	**55**	39.5	2.5	**39**
1000	47.1	25.9	**46.7**	32.7	2.4	**32.5**
1600	43.5	21.68	**43.43**	34.56	2.43	**34.25**

In DSR method For 560 samples 400 images are correct for texture and 290 images are correct for depth images. For 1600 samples 760 images are correctly recognized for texture and 620 are recognized for depth. From these tables we can say that the DSR method is slightly dominated in accuracy than SVD method. It shows a slight increase in recognition accuracy of both texture and depth images. As the number of samples increases it shows only small number of changes in accuracy. This means that the false rejection ratio and true acceptance ratio is high when using the algorithm described in this paper.

IV. CONCLUSION

Here the Comparison of SVD and DSR method of both texture and depth image is done. The result which are tabulated shows that both results shows a satisfactory recognition result, but the DSR method shows better recognition accuracy than SVD method for more number of samples. PCA is used to find the weighting coefficients of two methods. SVD reduces the mathematical complexities and it does not requires any computational time. In DSR method the relationship operator R is obtained mathematically. Here the entire algorithm is used for two modalities. These two methods shows a satisfactory results for LR face recognition than existing methods.

V. REFERENCE

[1] Interpolation-Based Image Super-Resolution Using Multisurface FittingFei Zhou, Wenming Yang, and Qingmin Liao, Member, IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 21, NO. 7, JULY 2012

[2].Fundamental Limits of Reconstruction-BasedSuperresolution Algorithms under Local Translation IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 26, NO. 1, JANUary

[3] Example-Based Super-Resolution,William T. Freeman, Thouis R. Jones, and Egon C. Pasztor Mitsubishi Electric Research Labs Image-Based Modeling, Rendering, and Lighting

[4] A Total Variation Regularization Based Super-Resolution Reconstruction Algorithm for Digital Video Michael K. Ng,Huanfeng Shen,Edmund Y Lam,and Liangpei Zhang 21 April 2007.

[5] Efficient sparse coding algorithms Honglak Lee Alexis Battle Rajat Rain Andrew Y. Ng Computer Science Department Stanford University Stanford.

[6] Image Enhancement Using Various Interpolation Methods RACST International Journal of Co mputer Science and Information Technology & Security (IJCSITS), ISSN: 2249-9555 Vol. 2, No.4, August 2012

[7] S. Baker and T. Kanade, "Hallucinating faces," in Proc. IEEE Int. Conf. Autom. Face Gesture Recognit., Mar. 2000, pp. 83–88.

[8] S. Biswas, G. Aggarwal, P. J. Flynn, and K. W. Bowyer, "Pose-robust recognition of low-resolution face images," IEEE Trans. Pattern Anal. Mach. Intell., vol. 35, no. 12, pp. 3037–3049, Dec. 2013

[9] Low Resolution Face Recognition Across Variations in Pose and illuminationieee transactions on pattern analysis and machine intelligence, vol. 38, no. 5, may 2016

[10] Z. Wang, Z. Miao, Q. M. J. Wu, Y. Wan, and Z. Tang, "Low-resolution face recognition: A review," Vis. Comput. - Springer, vol.30, no. 4, pp. 359–386, 2014.

[11] C. Liu, H.-Y. Shum, and W. T. Freeman, "Face hallucination: Theory and practice," Int. J. Comput. Vis., vol. 75, no. 1, pp. 115–134, 2007.

[12] S. Baker and T. Kanade. Limits on super-resolution and how to break them. IEEE Transactions on Pattern Analysis and Machine Intelligence, 24(9):1167–1183, 2002.

[13]B. Gunturk, A. Batur, Y. Altunbasak, M. Hayes, and R. Mersereau. Eigenface-domain super-resolution for face recognition. IEEE Transactions on Image Processing, 12(5):597–606, 2003 J. S. Park and S. W. Lee.

[8] An example-based face hallucination method for single-frame, low-resolution facial images. IEEE Transactions on Image Processing, 17(10):1806–1816,2008.

[14]X. Wang and X. Tang, "Hallucinating face by eigentransformation," IEEE Trans. Syst., Man, Cybern. C, Appl. Rev., vol. 35, no. 3,pp. 425–434, Aug. 2005.

[15] W. W. W. Zou, and P. C. Yuen, "Very low resolution face recognition problem," IEEE Trans. Image Process., vol. 21, no. 1, pp.327–340, Jan. 2012.

[16] Naveen S and DrMoni R S, "Multimodal Face Recognition System using Spectral Transformation of 2D Texture feature and Statistical processing of Face Range Images", ICICT 2014, Cochin, Kerala, Publisher: ELSEVIER Journal of Procedia Computer Science, December 2014, Volume-46.