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Face Recognition from Low Resolution Face Images; A Review

Roshnan.R. [1], Naveens.[2]

M Tech Student, Department of ECE, LBS Institute of Technology for Women Thiruvananthapuram, India[1]

Assistant Professor, Department of ECE, LBS Institute of Technology for Women Thiruvananthapuram, India[2]

Abstract: Face recognition is effective when input low resolutions are of high resolution (HR). Face images captured by surveillance cameras are of low resolution (LR) uncontrolled pose and illumination etc. There are several methods to improve the quality of low resolution image and perform the face recognition process. This paper primarily focuses on the review of those methods. The main objective is to find out and compare completely automatic approaches for recognizing low-resolution face images captured in uncontrolled environment. The approaches used are Discriminative super resolution, Hallucination using Eigen transformation, singular value decomposition, Simultaneous super resolution and recognition.

Keywords: Low resolution, hallucination, super resolution.

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 technique 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 person. 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 viewing area is maximized. But the face region in the scene is normally very small. When the person is notclose to the camera, face region will occupy less than a hundred of pixel. Recognition of such a very low resolution face images can be done by several methods. A review of some of the methods is being discussed in this paper.

The first method is low resolution face recognition using super resolution method. Super resolution means simply reconstruction of High resolution images from a low resolution image. In the case of face recognition this process is called as face hallucination. In very low resolution problem the image dimension is too small to reflect the error in high dimensional space. The reconstructed high resolution image may not be similar with input image. So a relationship learning based super resolution method is proposed. Next methods are hallucination using Eigen transformation and singular value decomposition .This are used to make the face identification and verification simultaneously and accurately.

Here section 2 briefing the various low resolution face recognition methods and section 3 gives the comparison of existing methods and section 4 gives the conclusion of all the methods.

II. BRIEFING OF THE VARIOUS LOWRESOLUTION FACE RECOGNITIONTECHNIQUES

A. Low resolution face recognition by super resolution.

Super resolution means simply reconstruction of High resolution images from a low resolution image. In the case of face recognition this process is called as face hallucination. The simplest way to increase the image resolution is direct interpolation but the performance is poor. Some of the super resolution algorithms are learning based. In learning based method to determine HR image input LR image and a down sampled matrix are given. But the solution of this method is ill posed. To overcome this problem MAP based approach is used. MAP based approach provides a convenient way to model a priori knowledge to constraint the solution. It can model the priori knowledge so that it can restrict the reconstruction of HR images in HR face image space. Mainly subspace methods are used to restrict the reconstruction of HR image space locating inside the face subspace. MAP based super resolution method is also used to reconstruct the eigenface coefficients for face recognition. Another method of super resolution is example based super resolution.

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Here the input low resolution images can be written as the linear combination of weights and LR examples. The reconstructed HR images are obtained by replacing LR examples by corresponding HR examples. This method assumes that the structure in LR subspace is same as that in HR subspace. But it may not be valid due to face variance. The MAP based and example based approach faces a constrained optimization problem called data constraints. If the data constraint is less than or equal to a positive error term which is used to control the dimension of solution space. Let the positive error term is equal to zero then solution space set occupies 98% of that in HR image space. This means that the data constraints cannot effectively restricts the target HR image solution space. Due to thisthere is a possibility that reconstructed HR image may have serious artifacts and not looks like the original person.

B. Low resolution face recognition by Discriminative superresolution

In learning based super resolution approach there are two image spaces for HR and LR images. Here the reconstructed HR image is down sampled to get the LR image in LR image space. Then find out the error between the obtained down sampled LR image and the input LR image. If the error is minimum then its dimension is too small and cannot reflect it in HR image space. To overcome this problem relationship learning based super resolution is proposed. Using this method the error is measured in high resolution image space so that better high resolution image quality image can be obtained. In this super resolution method first find out the relationship between two image spaces. Let R be the relationship between two image spaces then the reconstruction of HR image is obtained by taking the product of R and input LR image. R can then be determined by taking the minimum of mean square error between the N number of HR image and reconstructed HR images. The relationship operator R is obtained by a clustering algorithm. Clustering algorithm is simply clustering of LR and HR gallery images based on the gradient between images. Images with similar gradients are grouped into same cluster. Images are similar with in cluster and dissimilar between clusters. In this method R restrict the reconstructed HR images locating in an optimal subspace for minimizing the reconstruction error. Inorder to increase the discriminability of reconstructed HR image, discriminative constraint is added to the relationship leaning based SR in determining the optimal R. Based on minimum margin criterion (MMC) a discriminative constraint is designed. This is formulated by taking the difference between the summations of N number of reconstructed HR image clustered with the images from same class and far away from the images from other classes. The new discriminative super resolution can be obtained by integrating the normalized discriminative constrained obtained by MMC with relationship operator R determined in training stage.

C. Low resolution face recognition by Eigen transformation

This is a new face hallucination method using eigen transformation. Here principal component analysis(PCA) is applied to low resolution images. PCA is used to fit the input face image as a linear combination of the low resolution face image in the training set. Let a training set consist of M low resolution face images and corresponding HR images. In PCA first step is to convert the face image in training set to face vector. The image in training set is of NxN, then convert each image into a face vector of dimension N^2x1and each of M face vector are placed into face vector space. Once the face vector is converted in face vector space then normalize each of face vector. Normalization means removal of all the common features that the training images shared together. This is done to make each face vector with unique features.To find the common feature just take the average face vector ψ of each of the M facevectors. Then subtract average face from eachof face vector to get the normalized face vector $\phi_i=\Gamma_i-\psi$. Next step is to calculate theEigen vector. So covariance matrix C is needed to calculate Eigen vector, i.e. $C=\mathbf{A}\bar{\mathbf{A}}$. PCA is done by the decomposition of covariance matrix .The covariance matrix obtained having a dimension of N^2xN^2.That means N^2 number of Eigen vectors are obtained. In order to reduce the dimensionality and effect of noise from the needed eigen vector consider a lower dimensional subspace of face vector subspace, $C=\bar{\mathbf{A}}A$. Thus the covariance matrix obtained will have a dimension of MxM. Then select K best eigen faces such that K<M and can represent wholetraining set. Then convert lower dimension K eigen vectors to original face dimensionality and represent each face image as a linear combination of all K eigen vectors. Here in this approach the input image is a low resolution image. Perform the PCA method tothis input image as described above and represent each face image as a linearcombination of K eigenvectors.Let $\hat{c}$ describes the weight of each training face in reconstructing the input face . Let Γ_i and $\hat{h}_i$denotes the low resolution and high resolution images. Here replacing each low resolution image by its corresponding high resolution image using the same weight obtained from the low resolution input image. This high resolution sample is then added with the high resolution mean face. Obtained image after this mapping is expected to be an approximation of real high resolution face image.

D. Low resolution face recognition using S^2R^2 matching.

In this method both super resolution and feature extraction methods fits simultaneously. This method describes the problem of matching a low resolution probe image to a high resolution gallery of enrolled faces. There are two standard approaches to this problem. First, Low resolution probe image is super resolved to reconstruct a high resolution version and then matching between super resolved and gallery HR image is performed. Second, down sample the entire gallery

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and then perform matching in low resolution. The limitation of first is that the reconstructed HR image may not be in the same dimension as that of HR image in the gallery so correct matching is not possible. The limitation of second is that matching of two LR images cannot give better result. So the standard approach to classify LR image is to produce an estimate of the desired super resolved image. For the mathematical simplicity Tikhonov regularization is used to obtain the image by minimizing the objective function.

$$\|Bx-y^{p}\|^2+\alpha^2\|Lx\|^2 \qquad (1)$$

Here B is a matrix to convert HR image x to its low resolution version y.**α**is a regularization parameter. Lx is a vector of edge values. Here they proposed to classify the LR image while using the HR training set(F) in the framework that includes the class**ifier's metric.**

$$D(Fx^{p},Fx^{g})=\|Fx-f^{g\,k}\| \qquad (2)$$

Face identification and verification first step of this algorithm is to find the minimizer i.e. estimated probe LR image ,for that add Eqn.2 with a measure of difference between ideal features for the claimed class and the features that would be produced by the super-resolution result.

$$\|Bx-y^{p}\|^2+\alpha^2\|Lx\|^2+\beta^2\|Fx-f^{g\,k}\|^2 \qquad (3)$$

With the resulting estimation ,for the face verification a binary decision can be produced to check whether the image may accept or reject.

$$\arg\min w.q(\breve{x}^{p\,k}) \qquad (4)$$

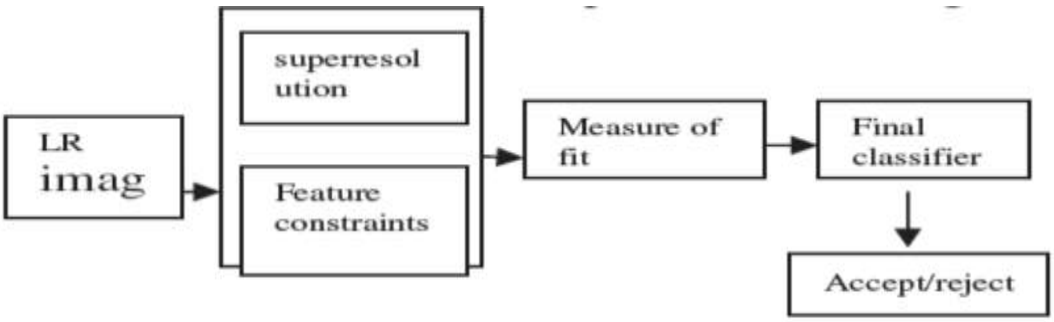
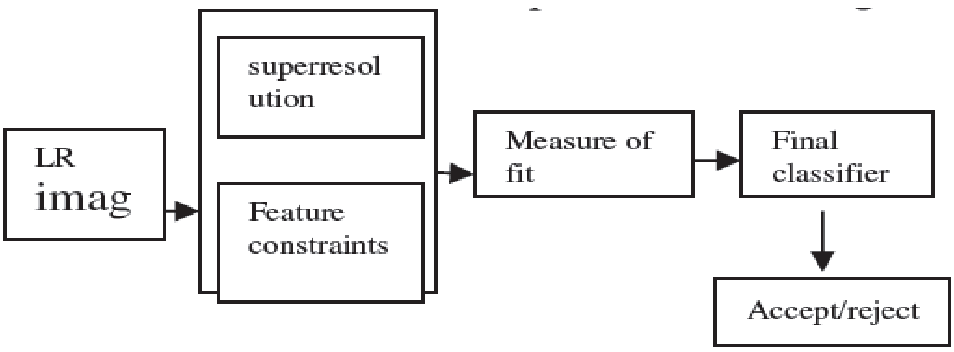
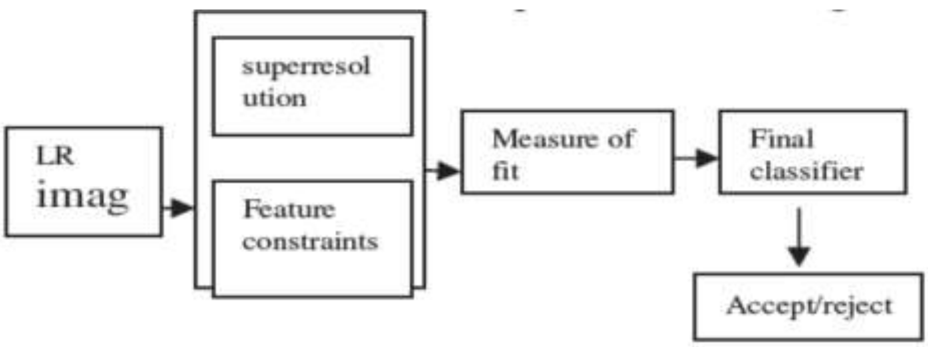


Fig 1.Simultaneous superresolution and rcognition.





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q($\breve{x}^{p\ k}$) is a vector of measure of fit. The firstcomponent measures the fit between the observed LR probe image and the LR version of resulting super resolved image. The second component measures the smoothness and the third component measures the difference between the feature the difference between the features derived from HR gallery images and those obtained from the super resolved image.

E. Low resolution face recognition using singular value decomposition.

This method is a face hallucination method using singular value decomposition. Here the hallucination and recognition of face images can be done simultaneously. Low resolution face recognition is carried out by super-resolving the LR input face first, and then performing face recognition to identify the input face .In order to improve the accuracy of recognition face verification and hallucination can be done simultaneously. Here the input probe image is a low resolution image. In the gallery database pair of LR-HR face images are available. The query face which are most similar to the input LR face are searched from the gallery database based on their singular values. The singular values of LR-HR images Are obtained by Equ.5.

$$A=UW\bar{V} \quad (5)$$

W represents the singular values which is a diagonal matrix. First, calculate the singular values of LR probe image and LR- HR gallery image. Then for verification, take the difference between singular values of probe image with the singular values of LR-HR image in the galley. For HR it is not possible because of its dimensionality. To make the input probe image as same dimension as that of HR, bicubic interpolation is required. Based on singular values they get Q faces which are most similar to probe image. If the difference between the singular values of the query and those of the claimed face in the database is larger than a certain threshold the claim will simply reject.

If the difference is smaller than the threshold, super-resolution will be performed based on the mapping models learned from the claimed LR-HR face pairs. The mapping matrices of the respective claimed face pairs are learned for estimating the high frequency information missed in the estimated HR faces generated by interpolating the two SVD matrices.

$$U_h = U_l' P_u \quad (6)$$

$$V_h = V_l' P_v \quad (7)$$

$$\tilde{P}_u = \left(U_l'^T U_l' + \varepsilon E\right)^{-1} U_l'^T U_h \quad (8)$$

$$\tilde{P}_v = \left(V_l'^T V_l' + \varepsilon E\right)^{-1} V_l'^T V_h \quad (9)$$

Ul and Vl denotes the interpolated LR image. After learning the mapping models M number of HR images which are most similar to probe image is obtained. Then take the difference between each of M HR images and corresponding HR face images in the database are computed in the Eigen space. Here the input LR face is assigned to the class of the face with smallest difference. The reconstructed HRIs obtained by,

$$\hat{U}_h = U_l' \tilde{P}_u \quad (10)$$

$$\hat{V}_h = V_l' \tilde{P}_v \quad (11)$$

$$I_h = \hat{U}_h \hat{W}_h \hat{V}_h^T \quad (12)$$

Then find the mean square error between each of HR image and reconstructed HR image. Thus the final estimation of high resolution face images can be more accurate and reliable. To further improve the visual quality of reconstructed HR image they also estimate the residual error matrix C̄. It consists of missing high frequency information.

C is obtained by taking the difference between HR gallery images and reconstructed HR image. Here they use Gaussian function to measure the similarity of two images. Thus the final reconstructed HR image is,

$$\bar{I}_h = \hat{I}_h + \bar{C} \quad (13)$$

III. COMPARISON OF EXISTING METHODS

Among all the methods for low-resolution face recognition discussed above, super resolution or face hallucination methods is the first technique to recognize the input probe images. There the simple interpolation technique or probabilistic techniques or example based techniques are used for super resolution of images. From that example based method is better because input image can be represented as a linear combination of other images. But the disadvantage of this method is that it takes more computation time and resultant image will not attain good visual quality. Next method is discriminative super resolution[10]. To reflect the error obtained in LR imagespace to HR space a relationship operator is formed. Relationship operator can be determined by a clustering algorithm. To make an optimal relationship operator discriminative super resolution method is used. Main advantage is that relationship operator is different for different subjects, so accuracy is better than other methods. If there is no proper algorithm is used then the chance of wrong clustering may occurs. Next method is Face hallucination using eigen transformation [9]. There principle component analysis is used. PCA is mainly used for dimensionality reduction. So using this method the dimension can be reduced to a lower limit. In PCA images can be converted in the form of face vectors and from that eigen vectors can be calculated. Inorder to represent an image, add the eigen vectors of the image with corresponding weights. This means it can be also represented as a linear combination of eigen faces. This method also consists of some mapping from LR to HR images. Due to these conditions this method also exhibit computational problems. Next method is S^2R^2 method[11]. It is simply super resolution method but feature extraction method also incorporated with it. So thismethod has an advantage that it can simultaneously fit both super resolution and feature extraction. Here distance metric is used to find the distance between some classes. This method face a problem when the estimated super resolved image should will not reach the same dimensional as that of HR gallery image. Next method is Low-resolution face recognition using SVD[13]. It is used for the simultaneous hallucination and recognition of low resolution face images. This scheme can retain the holistic structure and the high frequency details of face images. Here the advantage is That the verification and identification done simultaneously. This make the accuracy high and also it forms a residual matrix to add the missing high frequency components .It makes the reconstructed image with good visual quality. To investigate the problem of unconstrained face recognition, the Labeled faces in the wild (LFW)database is designed to evaluate the performance of different algorithms .The LFW consist of real world face images which are collected in the wild with different pose lighting condition, resolution, qualities, expression, occlusions etc. Based on this database the accuracy of each of the methods described above is tabulated here with LR faces of size 18x16, 16x14,14x12.

Table 1.Recognition accuracy of each methods.

Recognition methods	18x16	16x14	14x12
Eigen faces	39.23%	37.60%	34.09%
S^2R^2	55.70%	53.05%	51.88%
DSR	71.66%	70.85%	69.19%
SVD	72.15%	71.33%	69.50%

IV. CONCLUSION

All the methods which are described briefly are different LR face recognition methods.Eachmethod has both advantages and disadvantages. The comparison of all methods is described based on the LFW database with LR faces of different sizes. Among all other methods the singular value decomposition shows better accuracy.

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