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Face Recognition Using Relationship Learning Based Super Resolution Algorithm

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Abstract: The face recognition is an application which is used for identifying or verifying a person from a digital image. The common problem that often occurs while identifying the face from image is due to the low resolution in images especially when it is captured from a long distance. In automated face recognition system, this has always been a challeging problem. To overcome this problem, an approach to learn relationship between the high resolution space and the VLR image space for face is proposed. In this new approach the face recognition applications under the VLR problem is designed for good visuality. To create the Very Low Resolution (VLR) image corresponding to each of these High Resolution (HR) images, the HR images are resized to 64×48 pixels. The Very Low Resolution (VLR) of the face image is <16×12 pixels. The proposed system is implemented in MATLAB. The performance of the proposed system is tested. The proposed system is highly accurate and extremely fast in processing the image data. Experimental results show that proposed method outperforms existing methods. The VLR face recognition problem has been defined and discussed in this study. For good visual quality applications, a new data constraint that measures the error in the HR image space was developed and RLSR was proposed.

Key words: Very Low Resolution (VLR), Super Resolution (SR), Relationship-Learning based SR (RLSR), High Resolution (HR), Low Resolution (LR)

INTRODUCTION

The face recognition system is an application which is used for identifying or verifying a person from a digital image. One way is by comparing the selected face features from the image and a facial database. Several techniques have been implemented to carry out this application. Baker and Kanade developed an approach based on a Gaussian Pyramid and Laplacian Pyramid Model and employed the Bayesian theory to infer the super-resolved face image from the LR and used a steerable pyramid to extract multi-orientation and multi-scale information of low-level features from both the input LR face images and HR face images in database.

The increasing number of commercial and law enforcement applications requiring personal authentication (e.g., access control, surveillance of people in public places, security of transactions and human-computer interaction) and the availability of low-cost recording devices. Some reliable biometric recognition techniques are fingerprint and iris recognition. By using this technique it is intrusive and the success depends highly on user cooperation. But face recognition is non-intrusive, it is based on images which is recorded by camera. The user is not aware the existence of the face recognition system. The human face is the common characteristic used by humans to recognize other people and personal identification based on facial images is among all biometrics.

In this applications, camera is installed in a way but the viewing area is maximized but the face region is very small. To recognize a camera, it is to handle low resolution face image with variations such as pose, illumination and occlusion. Super-resolution from a single image by Glasner *et al.* (2009) proposed a unified framework for combining the two general approaches of super resolution. It show how this combined approach can be applied to obtain super resolution from as little as a single image (with no database or prior examples). Jia and Gong (2008) proposed the idea to learn a map from input low resolution images to target high resolution images based on example pairs of input and output images.

Deriving a High-Resolution (HR) image from the Low-Resolution (LR) one or a sequence of LR images provides a solution to these applications which is known as the Super Resolution (SR) imaging technique (Cristbal *et al.*, 2008). The SR algorithms can be categorized into two classes, i.e., multi-frame based approach (Qin *et al.*, 2009) and single-frame based approach which is also called learning-based approach. In the multi-frame based approach, the HR image is derived from several LR observations of the scene which are

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typically aligned with sub-pixel accuracy while in the learning-based approach an image database which includes LR and HR image pairs is used to infer the HR image from its corresponding LR input. Existing algorithm is proposed for Super Resolution (SR) for face image. By applying the algorithm the low resolution face image is reconstructed into high resolution face image. But this proposed algorithm works well when the image is in good illumination.

Zou and Yuen (2012) proposed the VLR problem using RLSR algorithm for 16×16 pixels. The face super resolution algorithm to address recognition of low resolution face image with non-linear variations. The proposed method learns the nonlinear relationship between low resolution face image and high resolution face image in (non-linear) kernel feature space (Zou and Yuen, 2010). When a person is not close to the camera then the resolution for the face image is <16×12 pixels. But it gives limited information and much information is lost.

To solve the VLR problem is to recover the missed information of the face image. Existing algorithms are classified into two approaches namely maximum a posteriori and example-based approaches. These two approaches perform error evaluation for the reconstructed. HR images which is called a data constraint. The data constraint is used for comparing the images by calculating the distance in the low-resolution image space for super resolution processing.

This study proposed a technique, Relationship-Learning based SR (RLSR) approach for solving the VLR problem and implemented by using MATLAB. The proposed scheme addresses the very low resolution problem in face recognition where the resolution of the face images to be recognized is lower than 16×12 pixels. This proposed scheme explains the novel approach to learn the relationship between the high-resolution image space and the VLR image space for face SR.

MATERIALS AND METHODS

Steps in face recognition: Figure 1 discuss the generic face recognition system consists of three main processing steps:

- Face detection means detecting and separation of face region from the given face image or video
- Feature extraction means which identifies and extract features of the submitted images. Features are local features such as lines, points or facial features such as eyes, nose and mouth
- Face recognition is by matching input image against the faces in database

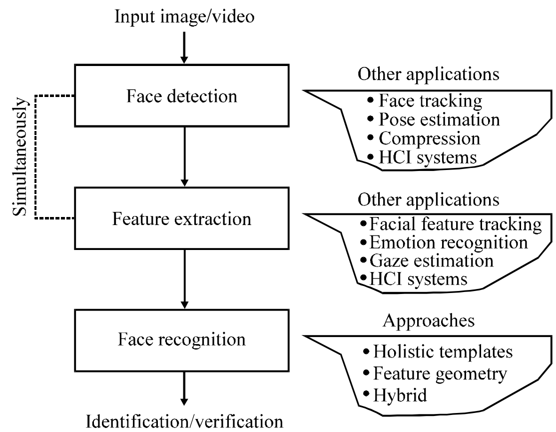

Fig. 1: Configuration of a generic face recognition system

Super resolution: Super Resolution (SR) is a technique that enhances the resolution of an imaging system. Super-resolution is a growing technique as a purely computational means to increase imaging sensors performance. It is unrealistic to assume that the super resolved image can recover the original scene o(x, y). A reasonable goal of SR is a discrete version of o(x, y) which has higher spatial resolution than the resolution of the LR images and which is free of the volatile blurs (deconvolved). The standard SR approach consists of sub pixel registration, overlaying the LR images on an HR grid and interpolating the missing values.

Though many techniques for image enhancement have been proposed, many realistic problems have not been solved satisfactorily. When an image is magnified or upsampled many times, blur or mosaic phenomena tend to occur thus diminishing the quality of the image. In case of wireless/remote surveillance, the resolution of obtained video is quite low due to limited bandwidth requirement in transmission or large data real time transmission and thus details for the people or object are not clear. In order to solve these problems, the super resolution techniques are employed. The idea is to construct a HR from a single or multiple LR images. In terms of pixels, the size of HR image is larger than LR image and the enhance techniques can magnify the LR image and increase image details making the magnified image close to the HR origin image. These techniques have become a popular research topic due to its broad applications in face recognition and surveillance.

The face similarity in the Very Low Resolution (VLR) image space cannot be an actual face similarity of HR face images. The existing SR algorithms may not be employed under the VLR problem. To solve the VLR problem, a Relationship Learning-based SR (RLSR) approach is proposed in this study. This algorithm makes use of the information available during the training phase and proposes a new learning-based face SR approach. Unlike most of the existing methods recovering the images directly from the VLR images and the training images, this algorithm first determines relationship between VLR and HR image spaces and then applies it on VLR images to recover the HR ones. The proposed new approach offers three additional advantages. SR algorithm can recover images with more details and handle the VLR problem better. The linearity clustering ensures data linearity in each cluster. Therefore, the linearity clustering-based relationship learning method can handle complex nonlinear case. The determined relationship, R is generic for all VLR testing face images.

Proposed system: The proposed SR algorithm can recover images with more details and handle the VLR problem better. The linearity clustering ensures data linearity in each cluster. Therefore, the linearity clustering-based relationship learning method can handle complex nonlinear case.

RLSR algorithm: There are several algorithms that exist to convert a low resolution image into a high resolution image. But these methods fail when a very low resolution image is used. Hence, an RLSR algorithm is proposed. Figure 2 gives the overall block diagram of the algorithm.

Training phase: The training phase consists of two steps, namely, linearity clustering and relationship learning. In the first step, a Clustering algorithm is proposed as a preprocessing step. After clustering, the Very Low Resolution (VLR)-High Resolution (HR) image pairs in each cluster are nearly linear, i.e., the relationship can be approximately represented by a matrix. In the second step, the relationship mapping from the VLR to the HR face image spaces within the cluster is determined.

The database: All the images are taken against a bright homogenous background with the subjects in an upright, frontal position. The files are in JPEG format. The size of each image is 64×48 pixels with 256 grey levels per pixel. Both male and female subjects are present in this database. To create the Very Low Resolution (VLR) image corresponding to each of these High Resolution (HR) images, the VLR images are resized to 16×12 pixels. To create the Very Low Resolution (VLR) image corresponding to each of these High Resolution (HR) images, the HR images are resized to 64×48 pixels. A test image pair is shown in Fig. 3.

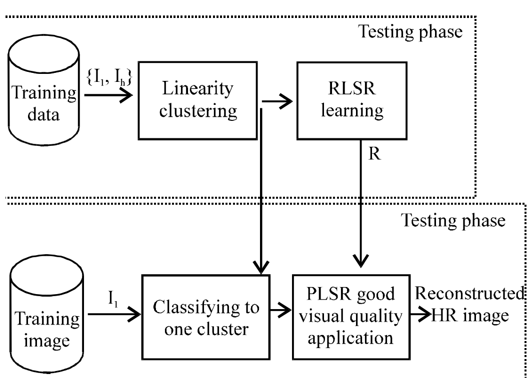

Fig. 2: Block diagram of RLSR

Linearity clustering: Clustering means assigning a set of objects into groups, so that the objects in the same cluster are more similar to each other than to those in the other clusters. The appropriate clustering algorithm and parameter settings depend on the data set. Here, a Linearity Clustering algorithm is proposed to ensure that the clustered training image pairs have a linear relationship. This Clustering algorithm reduces the complexity of the relationship learning process. Figure 4 shows the steps involved in the Clustering algorithm.

Maximizing the linearity of the clustered data pairs is equivalent to minimizing the difference of the gradient between the data pairs. Thus, the clustering algorithm utilizes the following two parameters:

- The gradient of the low resolution image
- The low resolution image

The contribution of the above two parameters is balanced by two constants-$\lambda 1$ and $\lambda 2$. Figure 5a depicts

Fig. 3: HR-VLR image pair

the HR images paired with their corresponding very low resolution image in the database. Once subjected to the linearity clustering algorithm, the images showing maximum similarity between their gradients are clustered together. This is depicted in Fig. 5b.

Relationship learning: Each cluster now holds the training image pairs, i.e., VLR-HR image pairs that have a linear relationship. Let R be the relationship mapping between between the VLR to HR face image spaces within the cluster, then $I_h^i = R(I_l^i)$. After determining R, the HR image can be recovered by applying R on the VLR image. After clustering, a matrix R is used to represent relationship mapping R. The relationship being represented as above from the image pair in each of the cluster, the relationship operator R can be derived as

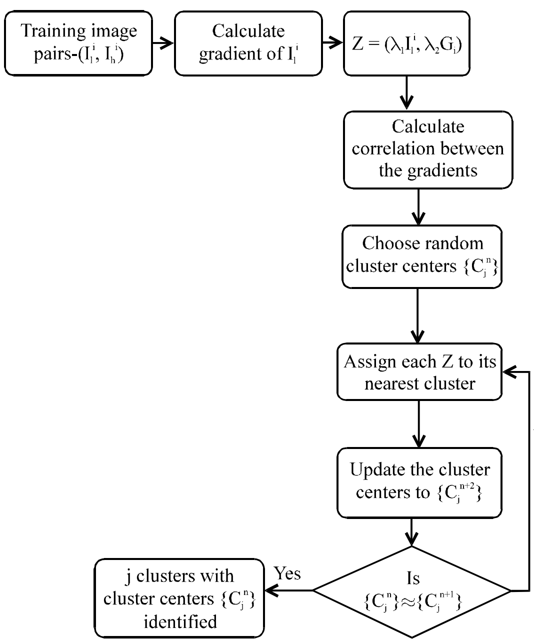

Fig. 4: Block diagram of the clustering algorithm

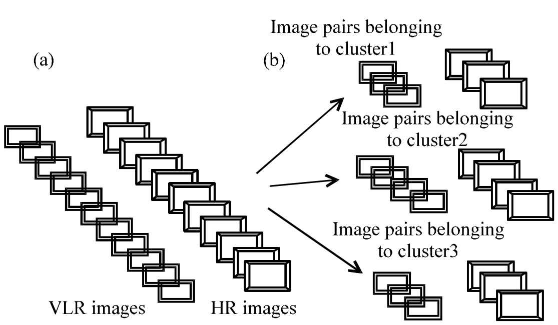

Fig. 5: a) VLR-HR image pairs in the database; b) clustered image

R = inverse $(LR)^*$HR. From this, the relationship matrix corresponding to each of the image pair is determined. The linear clustering aids in obtaining a unique relationship operator for each of the cluster. So, the relationship operators of the images in a particular cluster are extracted. The relationship operator corresponding each cluster-rcluster is selected such that reconstruction error is minimum.

Figure 6 gives a pictorial representation of how the unique relationship operator-rcluster, corresponding to each cluster is obtained. The straight forward method for this is minimising the reconstruction error. The reconstruction error is measured in the HR image space by the data constraint eR:

$$eR(I_h) = ||I_h - I_{h'}||$$

Here, I_h and I_l represent the HR and VLR image, respectively. A minimum mean square error is employed to learn R is represented as:

$$\min R \ 1/N \ \Sigma ||I_h^i - R I_l^i||$$

Utilizing the above two equations in the learning process ensures that the R cluster chosen incurs minimum reconstruction error. Another mechanism used to choose the optimum rcluster is by computing the average of the relationship operators belonging to each cluster.

Testing phase: The test image is of dimensions 16×12 pixels with 256 gray levels in each pixels, i.e., a VLR image

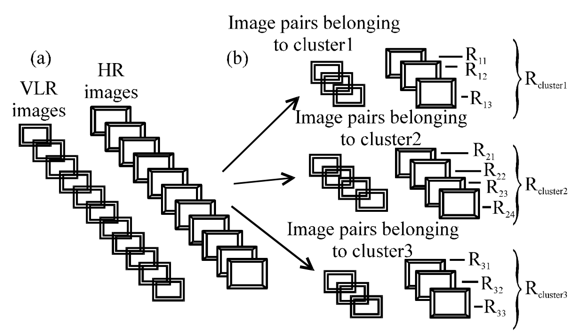

Fig. 6: Gives a pictorial representation of how the unique relationship operator-$R_{cluster}$, corresponding to each cluster is obtained. The straight forward method for this is minimising the reconstruction error. The reconstruction error is measured in the HR image space by the data constraint eR; a) VLR-HR image pairs in the database; b) clustered image pairs used to generate rcluster

is given as the test image. The gradient of this image is then calculated as G-test. Since, the parameter of the Linear Clustering algorithm used in the training phase is the gradient, G-test can be used to classify the VLR image into the appropriate cluster-i. Once the cluster-i is identified, the corresponding the R cluster-i is applied on the input testing image.

RESULTS AND DISCUSSION

The results in MATLAB the training images in the database are grouped into 3 clusters and outputs are displayed. The time complexity for the two relationship learning procedures is also compared.

Simulation of linear clustering: The training images on which clustering algorithm was applied is shown below in Fig. 7. The well aligned training images are normalized to the resolutions of 64×48 (HR) and 16×12 (LR). Since, there is no general method for aligning images with different poses, only frontal images are used. The number of clusters is chosen to be three and the following Fig. 8a-c show the cluster membership of each image.

The well aligned training images are normalized to the resolutions of 64×48 (HR) and 16×12 (LR). Since, there is no general method for aligning images with different poses, only frontal images are used. The reconstruction of the HR image from the VLR by the proposed RLSR algorithm. If the number of clusters = 5, the images in the training database is clustered as shown.

Table 1 in which each row represents a cluster group and their elements indicate the indices of the images present in the database. The reconstruction of the VLR test image when the training images are grouped into five clusters is shown in Fig. 10. The PSNR of this reconstructed image is computed to be 23 dB. If the number of clusters = 10, the images in the training database is clustered as shown.

Table 2 where each of the rows represents a cluster and its elements represent the indices of the images present in the database. The reconstruction of the VLR test image when the training images are grouped into ten clusters is shown below in Fig. 11. The PSNR of this reconstructed image is computed to be 30.8 dB. The code execution time in MATLAB for the two different Relationship learning procedures adopted in the algorithm is compared below for different database sizes. The values of time mentioned in the Table 3 are in seconds.

Table 1: Cluster index table with 5 clusters

Cluster index	Image indices
1	11
2	5, 7, 8
3	6
4	1, 2
5	3, 4, 9, 10

Table 2: Cluster index table with 10 clusters

Cluster index	Image indices
1	7
2	1
3	2
4	6
5	9
6	5, 8
7	4
8	10
9	11
10	3

Table 3: Comparison of time complexity

Procedures	Database size = 11	Database size = 21
Average R	3.50	6.23
Minimum error R	146.56	500.30

Fig. 7: Sample of training images

Fig. 8: a) Images in cluster1; b) Images in cluster2; c) Images in cluster3

Fig. 9: VLR test image

Fig. 10: Reconstructed output HR image

Fig. 11: Reconstructed output HR image

CONCLUSION

The VLR face recognition problem has been defined and discussed in this study. For good visual quality applications, a new data constraint that measures the error in the HR image space was developed and RLSR was proposed. Experimental results show that as the number of clusters in the algorithm increases the results obtained are more visually satisfactory. But as the number of clusters approaches the number of images in the database it causes over-learning (learning of redundant data). Results also show that the relationship operator obtained from averaging the relationships in each cluster consumes less time than the relationship operator got by minimizing the reconstruction error but at the cost of over learning.

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