GRAY-SCALE SUPER-RESOLUTION FOR FACE RECOGNITION FROM LOW GRAY-SCALE RESOLUTION FACE IMAGES

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ABSTRACT

Today's camera sensors usually have a high gray-scale resolution, e.g. 256, however, due to the dramatic lighting variations, the gray-scales distributed to the face region might be far less than 256. Therefore, besides low spatial resolution, a practical face recognition system must also handle degraded face images of low gray-scale resolution (LGR). In the last decade, low spatial resolution problem has been studied prevalently, but LGR problem was rarely studied. Aiming at robust face recognition, this paper makes a first primary attempt to investigate explicitly the LGR problem and empirically reveals that LGR indeed degrades face recognition method significantly. Possible solutions to the problem are discussed and grouped into three categories: gray-scale resolution invariant features, gray-scale degradation modeling and Gray-scale Super-Resolution (GSR). Then, we propose a Coupled Subspace Analysis (CSA) based GSR method to recover the high gray-scale resolution image from a single input LGR image. Extensive experiments on FERET and CMU-PIE face databases show that the proposed method can not only dramatically increase the gray-scale resolution and visualization quality, but also impressively improve the accuracy of face recognition.

Index Terms— Low gray-scale resolution, gray-scale super-resolution, face recognition

1. INTRODUCTION

The quality of images acquired by the cameras in a CCTV system might degenerate dramatically in image resolutions – both spatial resolution and gray-scale resolution, which may degrade computer vision system heavily. While a lot of work has been done to deal with spatial resolution degradation in the last decade as reviewed in [1], gray-scale resolution problem is rarely studied. Especially, in face recognition area, to our knowledge, no work has been done to investigate the Low Gray-scale Resolution problem.

By the term Low Gray-scale Resolution (Hereinafter abbreviated as LGR), we mean the phenomenon that the amount of valid gray-scales in the face image is less than a predefined threshold T. From the point of view of histogram, they are the gray-scales with none-zero (or larger than a threshold) frequency. Fig.1 shows some example LGR face images captured in a CCTV system. It is worth pointing out that LGR is different from dynamic range, since the gray-scales in a LGR image can be sparsely distributed in a relatively wide dynamic range.

Fig. 1: Due to dramatic lighting variations, face images captured in a CCTV system might be of Low Gray-scale Resolution (LGR).

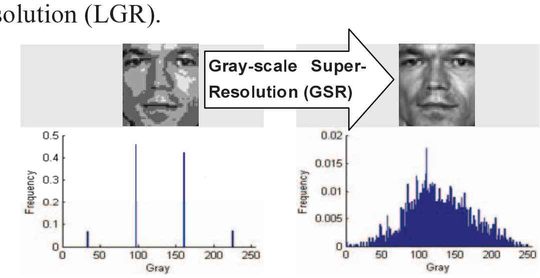


Fig. 2: Goal of this paper: Gray-scale Super-Resolution (GSR) from a simulated LGR face image (with histograms shown under the images before and after GSR proposed in this paper).

As shown in Fig. 1, LGR face images are lack of detailed appearance, which might lead to insufficient information for computer vision (CV) tasks. And even worse, LGR results in a lot of false contours along the iso-intensity lines. This phenomenon can heavily degrade performance of the edge-based CV approaches.

So, it is necessary to study how to recover an image of high gray-scale resolution (HGR) from an input LGR image, that is, to increase the amount of valid gray-scales occurring in the image. As illustrated in Fig. 2, we call this process *Gray-scale Super-Resolution* (and hereinafter abbreviated as GSR). From the images before and after GSR (as well as their histograms), one can see clearly the increase of valid gray-scales, richer texture, and removal of false contours.

In this paper, aiming at LGR problem in face recognition, we propose a learning-based GSR approach for recovering HGR face image from one single LGR input. The main contributions of this paper include:

1. The Low Gray-scale Resolution (LGR) problem and the Gray-scale Super-Resolution (GSR) process are defined and discussed explicitly for the first time.

2. Specifically, for face recognition (FR), we investigate experimentally the influence of LGR problem on the accuracy of a FR method and show its necessity and significance for further study. We also discussed its three categories of possible solutions.

3. A learning-based GSR approach based on Coupled Subspace Analysis (CSA) is proposed to recover the high gray-scale resolution image from single input LGR image. Extensive experiments on FERET [2] and CMU-PIE [3] database impressively show its effectiveness for both visualization and face recognition.

The rest of the paper is organized as follows. The LGR problem is analyzed in Section 2. A learning-based approach for GSR is detailed in Section 3. Experimental results are given in Section 4, followed by conclusion of this work.

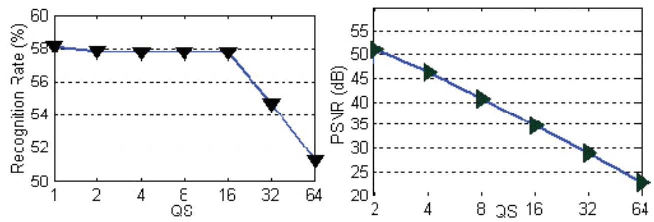
2. FACE RECOGNITION FROM LOW GRAY-SCALE RESOLUTION IMAGES: PROBLEM AND ANALYSIS

LGR actually implies two unexpected effects: one is the lack of details in appearance; the other is the false contours (i.e., iso-intensity lines). Both of them might lead to false classification. To quantitatively analyze the problem, in this section, some experiments are conducted to show how the accuracy of a face recognition system changes with reduced gray-scale resolution.

As shown in Fig. 2, simulated LGR images are generated by reducing the amount of gray-scales via intensity quantization with various quantization step (QS). LGS images with maximal possible amount of distinct gray-scales of 4, 8, 16, 32, 64, 128 and 256 corresponding to QS of 64, 32, 16, 8, 4, 2 and 1 are use in this study. The training, gallery and fafb subsets from FERET database [2] are used for generating the LGS images.

Firstly, evaluation is conducted to show how the degradation in gray-scale influences the accuracy of general face recognition methods. For the purpose of generality, in our experiments, the simplest face recognition method, i.e. nearest neighbor classifier based on correlation, is exploited. As is clearly shown in Fig. 3 (a), the face recognition performance drops dramatically with the decrease of gray-scales in images, especially when QS is larger than 16.

Besides evaluating the robustness of FR system for the gray-scale degradation of images, we also calculate the PSNR of images as a measurement of objective image quality. PSNR for one image is calculated as:



(a) (b)

Fig. 3: Recognition accuracy (a) and mean PSNR (b) vs. quantization step. Evident decline can be observed with the increase of quantization step (i.e., decrease of gray-scale resolution).

$$PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right) \tag{1}$$

where:

$$MSE = \frac{1}{m*n}\sum_{x=1}^{m}\sum_{y=1}^{n}\left[I_{LGS}(x,y) - I(x,y)\right]^2 \tag{2}$$

m and n are respectively the image height and width. I_{LGS} is the LGR image while I is the HGR image and R is the dynamic range of images, i.e. 256. From Fig. 3 (b), it can be noticed that there is a rapid decline of the mean PSNR across different LGR images.

Possible solutions to the LGR problem can be roughly grouped into three categories: gray-scale resolution invariant features, gray-scale degradation modeling and gray-scale super-resolution (GSR). Among which, GSR is intuitively most natural and general, which can also be used in other computer vision applications.

3. LEARNING-BASED APPROACH FOR GSR

Evidently, GSR is an ill-posed problem. Therefore, priors or more constraints must be introduced to obtain stable solutions. In case of face images, prior knowledge of face image distribution can be exploited to alleviate the ill-pose problem. Based on this idea, in this study, we present a coupled subspace analysis strategy to model the relationship between LGR images and HGR images.

3.1. Coupled subspaces analysis for GSR

For the convenience of the description below, we explicitly make some denotations in the next two sections before. Let $\Phi_{LGR} = \left(I_{LGR}^1\ I_{LGR}^2\ \cdots\ I_{LGR}^M\right)$ denotes the M LGR images in the training set and $\Phi_{HGR} = \left(I_{HGR}^1\ I_{HGR}^2\ \cdots\ I_{HGR}^M\right)$ denotes the corresponding M HGR images. All the images are N pixels with the same size of m rows and n columns. Φ_{LGR} and Φ_{HGR} separately forms the original LGR sample space X and an original HGR sample space Y.

As the LGR and HGR face images are appeared in the

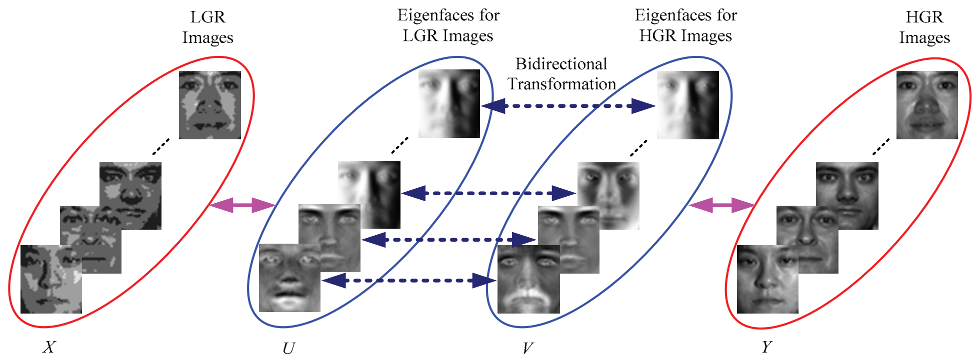


Fig. 4 Construct the in-between subspaces U and V from the Eigenfaces for the original sample spaces X and Y.

pair form, a coupled subspaces analysis (CSA) [4] approach will be appropriate for GSR from an LGR face image.

As is shown in Fig. 4, the construction of in-between subspace U and V for GSR takes the following two considerations into account:

1. In-between subspaces U and V should have satisfying reconstruction ability for the original sample spaces X and Y respectively.
2. There should be a bidirectional transformation between subspaces U and V, as X and Y are just the LGR and HGR versions for the same images.

Based on the first consideration, the Eigenfaces [5] from Principal Component Analysis (PCA), which has been shown to have excellent reconstruction ability [6, 7, 8], are utilized to construct subspace U and V. The in-between subspace U is computed by firstly calculating the eigenvectors V_{LGR} of the symmetric matrix L:

$$L = \Psi_{LGR}^{T}\Psi_{LGR} \tag{3}$$

where Ψ is the centralized LGR face images with the mean face $\bar{I}_{LGR}$ subtracted. And then the eigenvectors of the covariance matrix of Φ_{LGR} will be $\Psi_{LGR}V_{LGR}$. Similarly, the the eigenvectors for constructing subspace V can be calculated as $\Psi_{HGR}V_{HGR}$.

Once the two in-between subspaces U and V are constructed, the bidirectional transformation between them, as is shown in Fig.4, can be settled by the following steps:

1. The LGR images can be reconstructed using eigenfaces:

$$I_{LGR}^{i} = \left(\Psi_{LGR}V_{LGR}\right)W_{LGR}^{i} + \bar{I}_{LGR},\ i = 1,2,\cdots,M \tag{4}$$

where W is the weighting coefficient.

2. Directly replace Ψ_{LGR} and $\bar{I}_{LGR}$ with Ψ_{HGR} and $\bar{I}_{HGR}$ respectively in Eq. (4), we get an approximate reconstruction of the HGR image corresponding to the LGR one:

$$\tilde{I}_{HGR}^{i} = \left(\Psi_{HGR}V_{LGR}\right)W_{LGR}^{i} + \bar{I}_{HGR},\ i = 1,2,\cdots,M \tag{5}$$

3. A second projection, which is imposed in eigentransfromation [9], is performed to discard the non-face-like (noise) components in $\tilde{I}_{HGR}^{i}$:

$$W_{HGR}^{i} = \left(\Psi_{HGR}V_{HGR}\right)^{T}\left(\tilde{I}_{HGR}^{i} - \bar{I}_{HGR}\right),\ i = 1,2,\cdots,M \tag{6}$$

At last, the final estimate for HGR face images from GSR can be calculated as:

$$\hat{I}_{HGR}^{i} = \left(\Psi_{HGR}V_{HGR}\right)W_{HGR}^{i} + \bar{I}_{HGR},\ i = 1,2,\cdots,M \tag{7}$$

3.2. Benchmark algorithm

Naturally, HGR face images can be reconstructed in a regression framework by solving the following optimization problem:

$$\arg\min_{E}\sum_{i=1}^{M}\left\|I_{HGR}^{i} - EI_{LGR}^{i}\right\|_{L_2} \tag{8}$$

where E is the transformation from LGR images to HGR images, which is learnt from a training set. And then the GSR for input LGR images can be calculated as:

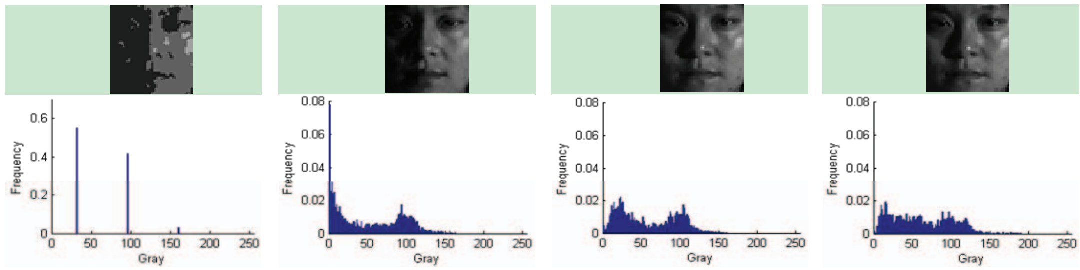
$$I_{HGR}^{i} = EI_{LGR}^{i}, i = 1,2\cdots M \tag{9}$$

4. EXPERIMENTS

Extensive experiments are performed on FERET FB and CMU-PIE face databases in order to verify the effectiveness of the proposed GSR approaches from the aspects of image visualization quality and face recognition performance.

A close look for GSR at one single face image is given in Fig. 5. There are great improvements in the number of gray-scale for both the benchmark and CSA-based GSR approaches; however, the number of gray-scale for images from CSA-based GSR is more close to that of the ground-truth. In practice, as much as 7 dB improvement in PSNR is obtained from CSA-based GSR approach. More GSR results from LGR face images can be seen in Fig. 6.

Face recognition experiments are also conducted on the GSR face images to verify the effectiveness of GSR for robust face recognition. As can be noticed in Fig. 7, there is a large disparity in the recognition performance between the benchmark and CSA-based GSR algorithms. The CSA-based GSR algorithm gets recognition performance close to the ideal bound which is the recognition performance on ground-truth face images. The reason that the benchmark algorithm results in satisfying PSNR but not so good



Input Benchmark CSA Ground-truth

Fig. 5 Improvement in gray-scale before and after GSR for one of the LGR face images under histogram perspective.

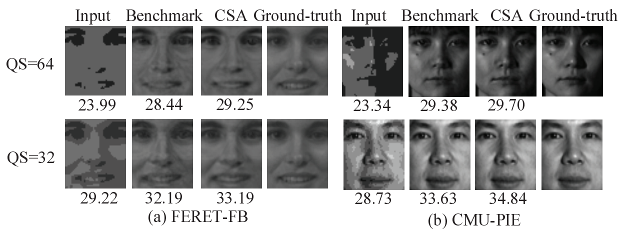
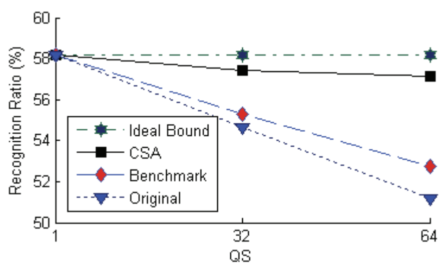
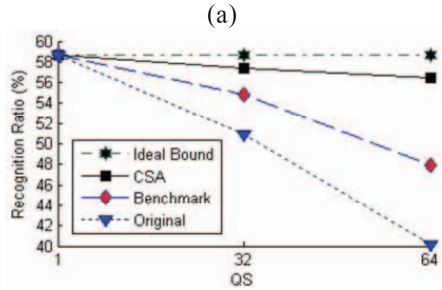


Fig. 6 GSR results on (a) FERET FB and (b) CMU-PIE face databases. The PSNR is shown below the face image.



(a)



(b)

Fig. 7 Face recognition performance on (a) FERET FB and (b) CMU-PIE face databases after GSR using benchmark and CSA algorithms.

recognition performance can be explained as that the transformation E learned in Eq. (8) is constrained to be only optimum for the reconstruction of training samples but lack of generalization.

5. CONCLUSION

In this paper, we made a primary investigation on the rarely concerned low gray-scale resolution problem, and proposed a learning-based gray-scale super-resolution (GSR) method to improve both the visual quality and face recognition performance from low gray-scale resolution images.

6. ACKNOWLEDGEMENT

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