Low-Resolution Iris Recognition via Eigen-Patch Super-Resoltuion

Abstract**—** In iris recognition systems low-resolution of an image will be a frequent factor as they reveal towards more relaxed acquisition conditions. Here, we evaluate a super-resolution algorithm based on Principal Component Analysis (PCA) Eigen-transformation of local image patches that enhance iris images. Each patch is reconstructed separately, providing better quality of enhanced images by preserving local information and reducing artifacts. Results show the supremacy of the presented approach over bilinear or bicubic interpolation, with the eigen-patch method being more spirited to reduce image resolution. Recognition performance can be done with the help of an iris matcher based on Log-Gabor filter and it declares that verification rates degrades more rapidly with bilinear or bicubic interpolation.

Keywords**—**Iris hallucination, iris recognition, eigen-patch, super-resolution, Principal Component Analysis

I. Introduction

Iris can be defined as one of the most accurate biometric feature for human identification [1]. Now-a-days iris recognition acquired more relaxed condition. Here we are addressing the problem of processing low-resolution images, for a long acquisition distances. Low-resolution image is an issue when images are compressed, but keep the dimension constant because it contain noise, artifacts etc.

The aim of super-resolution algorithm is not only to reconstruct the missing resolution but also increasing the recognition performance. It have previously employed to address the low-resolution problems of imaging system but now are used to increase both size and quality of a low-resolution images. Super-resolution improves the resolution of images, by combining multiple low-resolution to learn the lost high frequency components. Specifically there are two super-resolution approaches are exist: learning based and reconstruction based. Reconstruction based method directly operates on the pixel values of the low-resolution images. They are suitable for parallel implementation, but are limited to using a global translation in observation model. Learning based method synthesizes the frequency and produce visually pleasing images due to the high frequency component created by the method. But the problem is that when reconstruction error is high, the resulting high-resolution images are not look like the original one.

Here we apply super-resolution algorithm based on PCA Eigen-transformation [10] on local image patches. We take a low-resolution iris image as input then the high-resolution patch reconstructed as a combination of collocated patches.

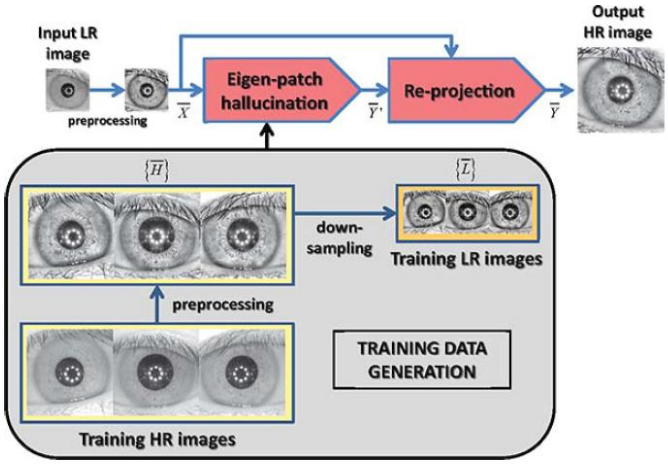

Fig. 1: Eigen-patch iris Hallucination system

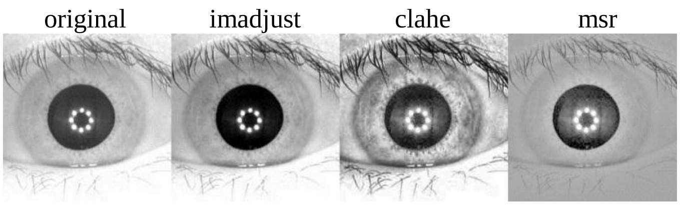

Fig. 2: Example of high-resolution images with different contrast enhancement approaches

Each patch has its own optimal reconstruction weights which, allowing more local image information. In our experiments, we used CAISA-IrisV4-Interval database [11]. All the images we used are NIR (near infrared). We handle recognition experiments based on LG wavelets and we can obtain that the proposed method provides better recognition performance than the bilinear or bicubic interpolation in low-resolution and show more resiliency to down-sampling. Our experiments performance shows EER below 6% for any down-sampling factor.

II. IRIS HALLUCINATION PROCEDURE

The structure of the hallucination method is shown in Figure 1. The method is based on the eigen-patch hallucination approach for face images of [10]. The system is described given next.

A. Eigen-Patch Hallucination

Taking an input of low-resolution iris image $\bar{X}$, it then first preprocessed to enhance contrast; after doing that, it is separated into N overlapping patches $\{\bar{x}\} = \{\overline{x_1}, \overline{x_2}, \cdot\cdot\cdot, \overline{x_N}\}$. Two super set of basis patches are obtained and computed for each low-resolution patch $\overline{x_i}$, separate from the input image $\bar{X}$, from collocated patches of a training database of high-resolution images $\{\bar{H}\}$. One of the super sets, $\{\overline{h_i^1}, \overline{h_i^2}, \ . \ . \ . \ , \overline{h_i^M}\}$, is obtained from collocated high-resolution patches. By decreasing (low-pass filtering and down-sampling) a low-resolution database $\{\bar{L}\}$ is obtained from $\{\bar{H}\}$, and the other super set, $\{\overline{l_i^1}, \overline{l_i^2}, \ . \ . \ . \ , \overline{l_i^M}\}$, is obtained similarly, but for $\{\bar{L}\}$. The sizes (number of images) of the training set are defined by M. The same contrast enhancement algorithm is applied to the high-resolution iris images of the training set before down-sampling. A PCA Eigen-transformation is then perform in each input low-resolution patch xi and using the collocated patches $\{\overline{l_i^1}, \overline{l_i^2}, \ . \ . \ . \ , \overline{l_i^M}\}$ of the low-resolution training images to obtain the optimal reconstruction weights $\overline{c_i} = \{\overline{c_i^1}, \overline{c_i^2}, \ . \ . \ . \ , \overline{c_i^M}\}$ of each patch. By allowing each low-resolution patch of the input image to have its own optimal reconstruction weights, the high-resolution patch will be closer to the input low-resolution patch, therefore more local information can be preserved and less reconstruction artifacts appear. Once the reconstruction weights $\overline{c_i}$ of each patch are achieved, the high-resolution patches are effected using the collocated patches of the high-resolution images of the training set $\{\bar{H}\}$. After averaging the overlapping regions the reconstruction coefficients of the input image $\bar{X}$ using the low-resolution patches is carried on to weight the high-resolution basis set, which outrun the preliminarily reconstructed high-resolution iris image $\bar{Y}'$. Additional details of this Eigen-transformation procedure can be obtained [10].

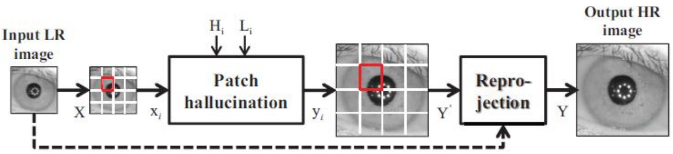

Fig. 3: Block diagram of patch-based hallucination

B. Image Re-projection

To make the output image is more look like to the input images, a re-projection step is applied. It redistributes the information from a set of input pixels to a set of output pixels. The image $\bar{Y}'$ is re-projected to $\bar{X}$ with the help of $\bar{Y}^{t+1} = \bar{Y}^t - \tau U(B(DB\bar{Y}^t - \bar{X}))$, here we defined U as an up-sampling matrix. The procedure stop until $|\bar{Y}^{t+1} - \bar{Y}^t| < \epsilon$ is smaller than the threshold. We use $\tau = 0.02$ and $\epsilon = 10^{-5}$ as difference threshold.

III. IRIS MATCHER

We perform matching experiments of the iris images by using Log-Gabor filters [12]. It first unwrap the iris region and normalizing the rectangle of 20×240 pixel using Daugman's rubber sheet model [13]. LG wavelet is applied in the phase of binary quantization to 4 levels. Matching can be done by using normalize Hamming distance [13]. It computes the lowest distance, which are consort the best match between two image templates. In the implementation of Libor Masek code, we are using default parameters. Manual annotations are used to obtain feature extraction and matching the corresponding iris region. Here incorporates noise are masked so that only significant bit are used for matching the iris images. We also used a post-processing process to remove false matching point.

TABLE I. Hallucination result with different down-sampling factors and different patches.

LR size (scaling)		bilinear	bicubic	PCA
115×115 (1/2)	psnr	34.7	34.6	35.15
	ssim	0.84	0.83	0.85
57×57 (1/4)	psnr	33.4	33.34	33.47
	ssim	0.80	0.79	0.80
39×39 (1/6)	psnr	32.7	32.5	32.72
	ssim	0.74	0.73	0.75
29×29 (1/8)	psnr	32	32	32.10
	ssim	0.71	0.71	0.72
23×23 (1/10)	psnr	32	31.9	32
	ssim	0.70	0.7	0.71
19×19 (1/12)	psnr	31.8	31.8	31.83
	ssim	0.70	0.7	0.71

IV. EXPERIMENTAL FRAMEWORK

In our experiment, we use CASIA-Iris Interval v4 database [11]. This database contains 2,639 NIR iris images of 280×320 pixels from 249 contributors whose are captured in 2 sessions with a close-up camera. We have total 396 different iris images (the numbers of the images are not constant). All iris images are 8 bit gray-level JPEG files, collected under near infrared illumination or synthesized. Here manual annotation is addressable, including iris circles and noise mask. We use bicubic interpolation for resizing all the images to have same sclera radius (we define the target sclera radius R=105 for the whole database). We then aligned the images by extracting a square region of 231×231 around the pupil center (about 1.1×R). Legally such extraction is not possible if the eye is close to an image side, the image is discarded. We have about 2,000 images after this process and use them for our experiment.

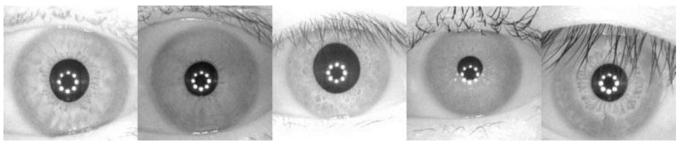

Fig. 4: Examples of iris images of the CASIA Interval v4 database with iris boundaries and eyelids

We first divided the aligned iris images into two sets. One is a training set from first 120 users and they are used to train for hallucination procedure. Other is a test set those are comprised of the remaining users used for validation. We conduct recognition experiments with the iris matcher to the test set. We reckon that each iris act as an individual user. Genuine matches are obtained by each iris images of a user with the remaining iris images of the same user, we avoid symmetric matches. Imposter matches are obtained by comparing first image of a user to the second image of the rest of the users. By using the approach we obtain about 2,601 genuine and 1,867 imposter scores.

We compare iris by using LG wavelets filter. LG first unwrapped the iris region to a normalize rectangle. The implementation we choose is from Libor Masek [12] and we use default parameters.

Matching between two images involves computing distances between all possible pairs of detected features and selecting as matching pairs those features whose nearest-neighbor is closer than some threshold. We set the range of the minimum distance otherwise more imposter matching occurs, that will degrades out performance result and increase the false acceptance rate.

V. EXPERIMENTAL RESULTS

Here we use 940 iris images of the set as high-resolution references images. We then down-sampled the iris images by using bicubic interpolation by factor of 2n (for example images are resized to 1/(2n) of the original size) and then we use all the down-sampled iris images as our input low-resolution images, from which hallucinated high-resolution images are extracted. We follow the down-sampled approach from the previous super-resolution techniques [14]. We down-sampled the images, due to lack of the database with low-resolution images and corresponding high-resolution reference images. We compare our results with bilinear and bicubic interpolation and also for three different contrast enhancement algorithm with the iris images.

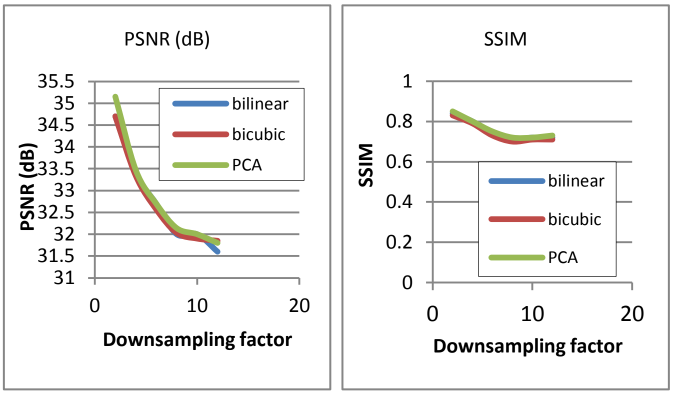

Fig. 5: Hallucination result with different down-sampling factors.

We measure the hallucination algorithm performance by calculation the PSNR (in dBs) and SSIM values between the original high-resolution images and hallucinated high-resolution images. We compare the result for different patch size, corresponding to 1/4, 1/6, 1/8, 1/10 of the low-resolution image size. We declare the patch size in proportion to the dimension of the low-resolution images. Here patch size is the valuable parameter.

After calculating the PSNR and SSIM values we obtain that hallucination method provides better performance than bilinear or bicubic interpolation even in very low-resolution. So we can conclude that it is more resilient as image resolution reduction. We also obtain that bilinear or bicubic have similar performance for small down-sampling factors but better performance is obtained at very low-resolution. We observe that when resolution drops, more artifacts appear in the images.

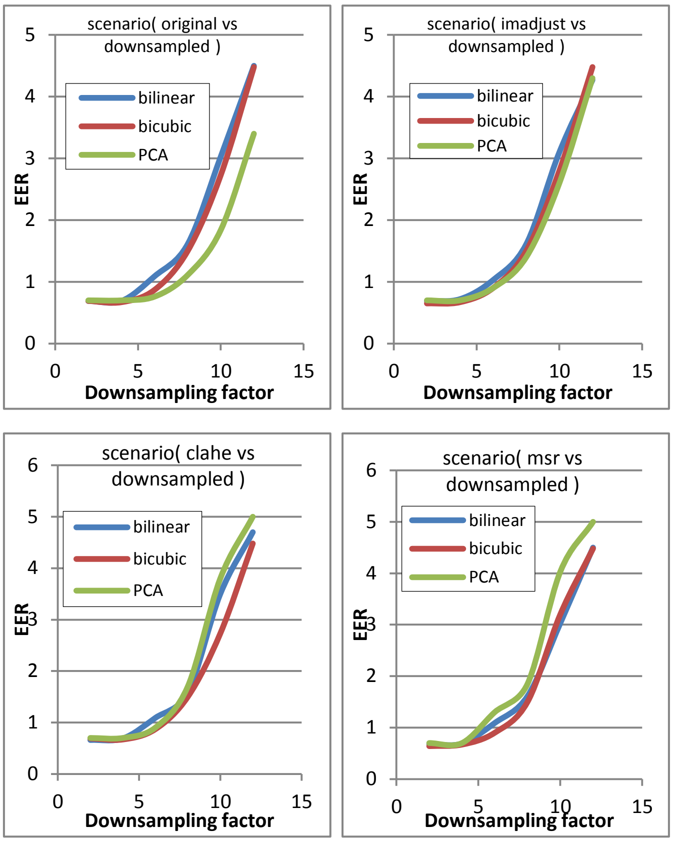

Fig. 6: Verification result (EER) of the four scenarios considered with different down-sampling factors (scenario 1 original vs down-sampled, scenario 2 *imadjust* vs downsampled, scenario 3 *clahe* vs down-sampled, scenario 4 *msr* vs down-sampled).

We measure the performance of the hallucination algorithm by reporting recognition using hallucinated high-resolution images. We use three different contrast enhancement images (*imadjust, clahe, msr*) for the experiments.

A. Contrast Adjust (imadjust)

It maps the intensity values in such a way that, by default, 1% of data is saturated at low and high intensities of the input data. It helps to remaps the image intensities to the full display range of the data. If make the best difference between black and white by sharping the image. (Matlab command *imadjust* is used).

B. *Contrast Limited Adaptive Histogram Equalization (clahe)*

For the experiments with *clahe* (Matlab command *adapthisteq*), the numbers of the tiles of the high-resolution images are 8×8 (rows×columns). The technique operates on only small data regions not on the entire images. Here each tiles contrast is enhanced, so that the histogram of the output region approximately matches to the specific histogram.

C. *Multi-Scale Retinex (msr)*

It combines the retinex dynamic range compression and color constancy with a color 'restoration' filter. *msr* provides better color rendition. We use Gaussian smoothing filter for *msr* which set the scale to 13, 25 and 38. The three scales are enough for the most images. We apply the Multi-Scale Retinex by using INFace toolbox v2.1.

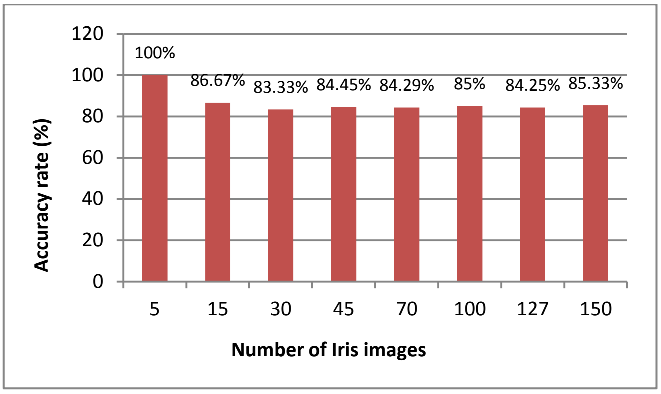

Fig. 7: Recognition result for different images.

With regard to the size of appropriate patch, it can be seen in Table 1 that the best performances are obtained with a big patch size (1/4 or 1/8 of the low-resolution image size, where 1/4 shows the best case for low-resolution). We can obtain that performance is not affected until down-sampling factor of 1/8.

VI. CONCLUSIONS

Since iris recognition system is image-based biometrics, it evolves the use of low-resolution images. In this paper, we apply PCA Eigen-transformation of local image patches that will increase the resolution of those images. Analyzing the experimental result on the database of NIR iris images, we conclude that our proposed approach is superior to bilinear or bicubic interpolation. It provides better quality reconstructed prototype with better local details and lower distortion. The approach provides more image resiliency even in low-resolution. We conduct matching experiments on hallucinated iris images based on LG wavelets. Since we use four types of images, we consider four scenarios. In Scenario 1 our proposed approach shows better performance than interpolation even in low down-sampling factors. Scenario 2 also shows our approach is superior to interpolation. But Scenario 3 and 4 shows interpolation is better than our approach. We are aware of the limitation of comparing our result with interpolation. Here we use only left iris images, but in future we will separate left and right iris images and implement right iris images. Since alignment is very demanding to appropriate hallucination output, we need to plan to analyze the sensitivity of the proposed approach to misalignment of the iris images. Our proposed technique provides linearity in finding local image patches and reconstruction weights. When we divide the images in patches the proposed approach will better cope with the artifacts, that will appears in low-resolution images.

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