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SINGLE FRAME SUPER RESOLUTION OF NONCOOPERATIVE IRIS IMAGES

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Abstract

Image super-resolution, a process to enhance image resolution, has important applications in biometrics, satellite imaging, high definition television, medical imaging, etc. The long range captured iris identification systems often suffer from low resolution and meager focus of the captured iris images. These degrade the iris recognition performance. This paper proposes enhanced iterated back projection (EIBP) method to super resolute the long range captured iris polar images. The performance of proposed method is tested and analyzed on CASIA long range iris database by comparing peak signal to noise ratio (PSNR) and structural similarity index (SSIM) with state-of-the-art super resolution (SR) algorithms. It is further analyzed by increasing the up-sampling factor. Performance analysis shows that the proposed method is superior to state-of-the-art algorithms, the peak signal-to-noise ratio improved about 0.1-1.5 dB. The results demonstrate that the proposed method is well suited to super resolve the iris polar images captured at a long distance.

Keywords:

Super Resolution, Iterated Back Projection, Iris recognition, SSIM, PSNR

1. INTRODUCTION

Iris recognition systems for long range captured iris images have wide range of applications such as remote surveillance and civilian identification. Because of uniqueness and stability [1] [2], Iris recognition has become a reliable way to validate the identity of a person. In security and surveillance systems, automatic person identification by identifying the iris in non-cooperative conditions has been important research topic. The existing systems normally work on iris images captured at a short distance. So, these systems are dependent on the cooperation of the users to get good quality iris images. This dependency can be overcome by using super resolution technique. This technique reconstructs the high resolution (HR) image using single or a sequence of low resolution (LR) images which could be taken from one or more cameras or could be frames of a video sequence [3] [4]. The SR algorithms are classified as interpolation-based, reconstruction based and example learning-based methods. Interpolation based methods are fast but these fail to recover high frequency details and produces artifacts. The reconstruction-based methods [4] [5] use smoothness priors and solve an ill-posed inverse problem of up-sampling, deblurring and denoising for high quality image. But these introduce watercolor-like artifacts and the quality of image degrades as the magnification factor increases. A reconstruction-based SR technique to restore multiple LR frames captured at a distance of 3 feet is proposed in [7]. This method uses autoregressive signature model between successive LR images is used while filling the sub pixels in the constructed HR image. The drawback of this method is entire eye image is used for registration, which is prone to errors due to iris contractibility and dilation properties. Hyperspectral image denoising is proposed by author [8] using spectral-spatial adaptive total variation model where spectral noise differences and spatial information differences are both considered in the process of noise reduction. Learning based SR methods can be characterized as non-probabilistic estimation. This method enhances the high frequency information by retrieving high frequency information from the training image dataset based on the local features of input LR images [9]. The author [10] proposes a single image SR approach by learning multi-scale self-similarities from an LR image itself. The proposed SR approach is based upon an observation that small patches in natural images tend to redundantly repeat themselves many times both within the same scale and across different scales. A novel efficient single image SR method for generic images based on learning a cluster of mapping relationships between the LR and HR feature subspaces is proposed by author [11]. The learned mapping functions effectively and efficiently transform the input image into the expected HR image. The author is also proposed a fast yet effective non-local means based SR enhancement algorithm for reducing edge artifacts by exploiting similarity structures in the resultant image.

Section 2 discusses the proposed EIBP algorithm to super resolute the iris polar images. The experimental results and analysis are discussed in Section 3 followed by conclusion in Section 4.

2. PROPOSED METHOD

The face and eyes are extracted by using AdaBoost-based [12] [13] face and eye-pair classifiers. It detects the face region first and then eye-pair detector is applied on focused face region. This method improves the robustness to detect the eye region by releasing the region of interest at each level. The output of eye detector is processed further by classifying eye into right or left group. This classification is achieved by partitioning the width of the detected eye region. The iris is segmented from eye images using Hough Transform method [14]. The extracted iris is converted into polar form [15]. This polar image is super resoluted using proposed algorithm. The proposed iterated back projection based resolution enhancement algorithm is primarily inspired by the recent work of [16] [17]. The modified IBP algorithm is as below.

1. Divide LR iris polar image in patches having size 20×20 pixels. Select the patch L_{CF} for SR process.
2. Set iteration index $n = 1$, Up-sample L_{CF} by up-sampling factor u to obtain U_{CF} using conventional algorithm.

$$U_{CF}^{n} = \uparrow_{u} L_{CF}^{n} \quad (1)$$

3. Decimate the convolution of U^n_{CF} with matrix of Gaussian Point Spread Function (P) to get simulated low resolution image.

$$S^{n} = \uparrow_{d}\left(U_{CF}^{n} \times P\right) \quad (2)$$

For down sampling, adapt Lanczos3 low-pass filtering to eliminate high-frequency components to prevent from the aliasing effect. The reconstruction kernel of Lanczos3 one-dimensional (1-D) low-pass filter is given as,

$$L(x) = \frac{3\sin(\pi x)\sin\left(\frac{\pi x}{3}\right)}{\pi^2 x^2} \quad (3)$$

Matrix P at position (x, y) is computed using,

$$P_{x,y,\sigma} = \frac{1}{2\pi\sigma^2} e - \frac{x^2+y^2}{2\pi\sigma^2} \quad (4)$$

P is chosen over interval [-2, 2] and σ = 0.5

4. Subtract with from original low resolution image to get error E^n_{CF}

$$E_{CF}^{n} = \left\| L_{n}^{CF} - S^{n} \right\| \quad (5)$$

Check if E_{CF} < maximum error or n < maximum iteration, then

$$U_{HR}^{n+1} = U_{CF}^{n} + BM \times \uparrow\left(E_{CF}^{n}\right) \quad (6)$$

where BM = Laplacian of Gaussian back projection matrix

$$BM = \begin{bmatrix} -1 & 2 & -1 \\ 2 & 8 & 2 \\ -1 & 2 & -1 \end{bmatrix}$$

else-Terminate with U^n_{CF}. Maximum error = E_{CF}.

5. Repeat step 1 to 6 for all the frames.
6. At n^{th} iteration, the output is the enhanced image.
7. The high pass image enhancement filter

$$hp = 1 - \left(\frac{3\sin(\pi x)\sin(\pi x/3)}{\pi^2 x^2}\right) \quad (7)$$

8. The enhancement equation is expressed as:

$$U_{HR}^{n+1} = \left(\gamma \times hp\right) - U_{HR}^{n} + \left(\gamma \times E_{HR}^{n}\right) \quad (8)$$

where γ = decay function

Repeat above steps for all patches. Combine the reconstructed patches into one global image which is super resolved image. The noise present in SR image, if any, is removed by low pass filter. The Gaussian Low-Pass Filter (GLPF) is one of the most simplistic post-processing methods for removing noise. Although it is simple, it has been proved to be useful in many practical situations. The frequency response of a GLPF can be described as:

$$H(u,v) = e^{-D^2(u,v)/2\sigma^2} \quad (9)$$

where, $D(u,v)$ is distance from the center of the frequency spectrum and σ decides cutoff frequency of GLPF. The size of the GLPF is 3×3 with σ = 0.5.

3. RESULT

The experimental results of the proposed approach are demonstrated by analyzing the performance of enhanced IBP. The performance is evaluated on two counts: PSNR and SSIM [18]. The algorithm is implemented using Matlab2009a on Intel Core i3 machine with processor speed of 1.8GHz and RAM size of 4 GB. The performance of proposed method is evaluated on CASIA long range iris image database [19]. The CASIA database consists of 140 person's faces and more than 10 images of each person. The ages of the people span from 19 to 61. The selection of number of iteration plays key role in super resolving the images. The selection of this is determined by analyzing the quality parameters. The analysis of selection of iteration is as shown in Table.1. The PSNR and SSIM of proposed method improve as number of iteration increases but it increases the execution time. At a lower iteration, the image quality is not much good, but it super resolute the image in very less time. After iteration 100, there is small increase in image quality but at a cost of more execution time. Based on the analysis, iteration is set to 100 for the proposed method.

The proposed algorithm is tested for 1100 iris polar images. The resolution of the extracted iris polar image is 300×20. The up-scaling factor 2 is considered during the super resolution process. After super resolution, the size of the polar image is 600×40. Due to limitation of space, ten person's iris polar images performances are discussed. The Fig.1 shows ten input iris polar images. The proposed method is analyzed by comparing with the results of the state-of-the-art algorithms IBP [20] and Bin Zhao method [21] for iris polar images as shown Table.2. It can be seen that, the proposed method gives comparatively good results than the state-of-the-art algorithms.

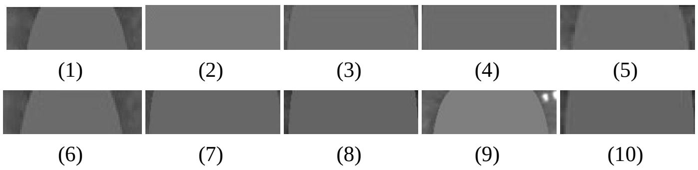

Fig.1. Long range captured input iris polar images

Table.1. Analysis of image quality for iteration

Iteration	Image1			Image2			Image3		
	PSNR	SSIM	Time	PSNR	SSIM	Time	PSNR	SSIM	Time
140	35.26	0.812	33	32.85	0.809	36	31.76	0.794	35
120	35.11	0.811	26	32.442	0.804	28	31.36	0.791	30
100	**34.97**	**0.81**	**22**	**32.44**	**0.803**	**23**	**31.36**	**0.788**	**25**
80	34.06	0.794	19	31.06	0.786	20	29.84	0.757	21
60	32.81	0.781	17	30.51	0.759	17	28.1	0.719	18
40	30.67	0.752	12	29.13	0.735	11	26.23	0.698	12
20	29.55	0.719	11	28.27	0.711	8	25.39	0.655	9
0	26.36	0.688	9	26.85	0.692	5	24.97	0.629	7

The images are super resoluted using proposed method is further tested for up-sampling factors (Λ) = 4 and 6 as shown in Table.3. From the Table.3, it can be seen that the quality of super resolved image decreases as the up-sampling factor increases. As the up-sampling factor increases the PSNR and SSIM of proposed method reduces, but compared to state-of-art algorithms the proposed method gives good quality image.

Table.2. Analysis of proposed method

Image No.	Bicubic		IBP [20]		Bin Zhao [21]		Proposed Method	
	PSNR (dB)	SSIM	PSNR (dB)	SSIM	PSNR (dB)	SSIM	PSNR (dB)	SSIM
1	31.54	0.653	32.29	0.725	34.10	0.749	34.97	0.783
2	29.06	0.622	31.02	0.713	32.27	0.726	32.44	0.754
3	28.7	0.596	29.91	0.708	30.89	0.719	31.36	0.723
4	25.58	0.493	27.69	0.659	29.56	0.684	30.76	0.696
5	26.19	0.501	29.37	0.688	29.84	0.703	30.51	0.711
6	26.88	0.512	28.22	0.671	29.67	0.692	31.15	0.704
7	28.39	0.567	29.85	0.695	30.12	0.708	31.29	0.716
8	27.67	0.554	29.01	0.682	29.95	0.694	30.73	0.704
9	28.55	0.589	29.76	0.685	30.29	0.702	31.64	0.709
10	26.89	0.512	28.51	0.657	29.43	0.681	30.42	0.695

Table.3. Analysis of proposed method for different up-sampling factors

Image No.	Λ	IBP [20]		Bin Zhao [21]		Proposed	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
1	4	28.51	0.583	29.11	0.621	31.36	0.659
	6	25.37	0.511	26.83	0.529	29.86	0.573
2	4	25.74	0.595	26.83	0.622	29.58	0.643
	6	23.37	0.498	24.65	0.506	27.39	0.519
3	4	26.39	0.545	27.85	0.586	29.71	0.627
	6	24.35	0.519	25.03	0.549	27.01	0.603
4	4	25.11	0.522	26.54	0.553	28.45	0.588
	6	23.75	0.513	24.08	0.529	26.00	0.542
5	4	25.54	0.536	27.06	0.584	28.11	0.612
	6	24.89	0.502	26.17	0.546	26.14	0.575
6	4	26.53	0.535	27.47	0.578	29.64	0.609
	6	23.57	0.509	25.79	0.529	27.55	0.565
7	4	26.33	0.553	27.18	0.619	28.79	0.685
	6	25.12	0.516	26.56	0.548	26.73	0.614
8	4	24.28	0.567	26.82	0.628	28.37	0.672
	6	22.16	0.532	25.65	0.559	26.03	0.593
9	4	26.59	0.596	28.39	0.628	29.56	0.677
	6	24.27	0.505	25.08	0.562	26.88	0.588
10	4	25.38	0.546	27.22	0.602	28.13	0.613
	6	22.55	0.521	23.49	0.523	26.19	0.566

4. CONCLUSION

In this paper, enhanced iterated back projection algorithm is implemented to super resolute the iris polar images. The performance analysis of proposed algorithm is done by comparing the PSNR and SSIM of images obtained using state-of-the-art algorithms. The experimental results show that the proposed algorithm gives better PSNR and SSIM than the state-of-the-art algorithms. The proposed method enhances the iris image by increasing its resolution twice and gives good image quality at higher number of iteration. It has been also observed that, as the up-sampling factor increases, the SNR and SSIM of proposed method decreases, but it is good compared to other algorithms. In the future work, features of super resolved iris images are extracted and classifiers are used to classify the iris images.

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