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Iterated Back Projection Based Super-Resolution for Iris Feature Extraction

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Abstract

In this paper, Iterated Back Projection and median estimators super-resolution algorithms, are implemented to increase the resolution of low resolution (LR) iris images. These two algorithms are analysed by extracting the Gray Level Co-occurrence Matrix (GLCM) features of super resolute iris images. The GLCM features of super-resolute iris images are compared with GLCM features of original iris images. The quality of resolution of enhanced image is measured using different image quality measures. It has been seen that the GLCM features of reconstructed images using above algorithms matches with that of original iris image and also the quality of enhanced image remains same.

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Keywords: Super-resolution, Iris, IBP, Robust, Quality Measures, GLCM ;

1. Introduction

The iris recognition plays significant role is many applications in the field of security, border control, surveillance, etc. Significant amount of research work is being done for identifying the person by using recognizing the iris. Now, there is a demand for recognizing the iris image captured at a long distance. A lot of research has been

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going on to recognize the iris at a distance more than 1 meter, called as Long Rage Iris Recognition. The major problems in recognizing the iris at a distance are: low resolution and illumination noise, which decreases the iris recognition success rate.

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These problems can be overcome by using Super-resolution technique[1, 2], which enhances the resolution by reconstructing lost high frequency information. The short range captured iris images are used to analyses the performance of IBP and robust algorithm. In this paper, the performance analyses of IBP and Robust super-resolution algorithms for iris feature is carried out by extracting the GLCM features low resolution iris image and GLCM features of the super-resolute iris image.

Section 2 discusses the literature survey. The super-resolution algorithm, Iterated Back Projection and Robust algorithms are discussed in section 3. The result and conclusion are discussed in section 4 and 5.

2. Literature Survey

The super-resolution techniques to reconstruct low resolution iris frames captured at distance around three feet are discussed by Falmy[3]. The HR images are reconstructed based on autoregressive model between successive LR in filling the sub-pixels in the constructed HR images. Image deblurring, useful in less intrusive iris capture systems, have been proposed to extend the effective range for iris capture [4, 5, 6,7]. Jianchao Yang et. al proposes[8,9] a method sparse signal representation based super-resolution. Thomas Kohler[10] proposes a framework in which multiple low-resolution video frames in retinal fundus imaging are used to reconstruct high-resolution fundus images. C. T. Dang[11] proposed a novel approach in which single image reconstruction is based on linear diverse approximation of the high-resolution image-patch space.

3. Super-Resolution Algorithms

Super-resolution (SR) is an image processing method that learns or reconstructs missing high-frequency information in order to increase the resolution of an imaging system. It is possible to reconstruct the original image, by choosing a magnification factor, L, for the desired high resolution (HR) image, where L represents ratio of high resolution image to low resolution (LR) image. The value of the magnification factor will depend on the number of non-redundant LR images that are available. Equation (1) shows observation model that relates the original to HR image.

$$Y_k = DB_kM_kX + N_k \qquad k = 1, 2, 3, \dots K \quad \text{- (1)}$$

where, D is a down-sampling operator, B_k contains the blur for the k^{th} LR image, M_k holds the motion information that transforms the k^{th} LR image onto the HR image lattice, and N_k is the noise in the k^{th} LR image. The Y_k LR images and HR image X consists of N and PN pixels respectively, where the integer $P > 1$ is the factor of enhance in resolution. Y_k and X are arranged as $N \times 1$ and $PN \times 1$ vectors respectively. The effects of blurring, warping [12] and down-sampling can be combined into a single $N \times PN$ system $B_{k(s_k)}$ matrix, where each row in matrix $B_{k(s_k)}$ maps the pixels in the HR image to X one pixel in the LR image Y_k. The equation (1) can be written as

$$Y_k = B_{k(s_k)}X + N_k \qquad \text{- (2)}$$

Given equation (2), the super resolution problem is to find an approximation of the HR image X from the set of LR images Y_k using prior information about $C_{(s_k)}$ warping matrix generated by the motion vector (s_k), N_k and X. Iris image resolution is enhanced by using Iterated Back Projection and median estimators algorithms are discussed as below.

3.1 Iterated Back Projection

The iterated back projection algorithm is discussed as below.

- The HR image is estimated by back projecting the difference between[13] simulated LR images and the observed LR images. Initially, the LR input images are used to generate the HR image by decimating the pixels.
- During iteration, the high resolution approximation is re-sampled in the grids of the input images. The difference (error) between the input image and re-sampled image projected back to the high-resolution grid.
- Check the energy of the error.
- Repeat above steps iteratively until the energy of the error is minimum, or until the maximum number of allowed iteration is reached.
- The down-sampling procedure decreases the sampling frequency which generates distortion in high frequency components and the aliasing problem. To overcome this, HR image is filtered using Gaussian filter.

This method is expressed mathematically as below.

$$f^{n+1} = f^{n} - \lambda \Delta L(X) \qquad - (3)$$

where

$$\Delta L(X) = \sum_{k=1}^{n} G_k = C_k^T H_k^T A_k^T (A_k H_k C_k X - Y_k) \qquad - (4)$$

Here,

- f^{n+1} is SR image resulting from $(n+1)^{th}$ iteration.
- f^{n} is SR image in the $(n)^{th}$ iteration.
- λ : Gradient step

The iris images are super resoluted to different resolution and the features are extracted to compare with features of original image.

3.2 Robust Super-Resolution

Different outliers like parallax, moving objects, etc., during capture of an image. These outliers are inconsistent with an imaging model. The robust super-resolution algorithm[14] filters out such outliers at a low computational cost. To bring in robustness into the process, equation (4) is modified with a scaled pixel-wise median.

$$\Delta L(X)(x, y) = n.\, median\{B_k(x, y)\}_{k=1}^{n} \qquad - (5)$$

This method is used to super-resolute the images captured using low resolution cameras.

3.3 GLCM Feature Extraction

Texture can be considered a surface property of every object. It can be considered as "organized area phenomena". It is very difficult to describe a texture due its high variation. The GLCM [15, 16] is a method of extracting statistical texture features of second order. The frequency in which pairs of pixels with specific values and in a specified spatial relationship occur in an image is put in a matrix and statistical features are extracted from this matrix. This calculation gives the function which characterizes the texture of an image. The number of rows and columns in the matrix is equal to the number of gray levels, *G*, in the image. The matrix element $P(i, j)$ is entry in the normalized gray-tone spatial dependence matrix. They are as below.

- **Contrast**

$$\text{Contrast} = \sum_{n=0}^{G-1} n^2 \left\{ \sum_{i=1}^{G} \sum_{j=1}^{G} P(i, j) \right\} \qquad - (6)$$

where *n* stands for the number of distinct gray levels in the quantized image. It gives the amount of local changes in the image.

- **Inverse Difference Moment:**

$$\mathrm{IDM} = \sum_{i=1}^{G-1}\sum_{j=1}^{G-1}\frac{1}{1+(i-j)^2}P(i,j) \qquad -(7)$$

It counts image homogeneity by assuming higher values for minimum gray tone differences in elements.

- **Entropy**

$$\mathrm{Entropy} = -\sum_{i=1}^{G-1}\sum_{j=1}^{G-1}P(i,j)\times log\big(P(i,j)\big) \qquad -(8)$$

This gives the disorder or complexity of an image.

- **Correlation**

$$\mathrm{Correlation} = \sum_{i=1}^{G-1}\sum_{j=1}^{G-1}\frac{(i\times j)\times P(i,j)-(\mu_x\times\mu_y)}{\sigma_x\times\sigma_y} \qquad -(9)$$

where μ_x, μ_y, σ_x, σ_y are the means and standard deviations of P. It gives gray level linear dependence between the pixels at the specified positions relative to each other.

- **Energy**

$$\mathrm{Energy} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}P(i,j)^2 \qquad -(10)$$

It gives information of repetitions of pixel pairs.

- **Autocorrelation**

$$\mathrm{Autocorrelation} = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(i,j)P(i,j) \qquad -(11)$$

This feature tells about the size of the tonal primitives.

The image quality is measured by using below image quality measures for a distorted image with reference to an original image.

- **Mean Square Error (MSE)**

Mean squared error (MSE) measures the average of the squares errors between original image (I) and reconstructed image (K).

$$\mathrm{MSE} = \frac{1}{m\times n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[\mathrm{I}(i,j)-\mathrm{K}(i,j)]^2 \qquad -(12)$$

- **Peak Signal to Noise Ratio**

PSNR is logarithmic ratio of maximum possible pixel value of the image to MSE

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{\mathrm{MAX}_I^2}{\mathrm{MSE}}\right) \qquad -(13)$$

- **Normalized Correlation (NC)**

The correlation function quantifies closeness between two images and it can be calculated by using equation (14)

$$NC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}I(i,j)\times K(i,j)}{\sum_{i=1}^{m}\sum_{j=1}^{n}I(i,j)^2} \qquad -(14)$$

- **Mean Difference**

This is an average of difference of two images

$$\text{Mean Difference} = E[|I - K|] \quad -(15)$$

- **Maximum Difference (MD)**

$$MD = MAX[|I(i-j) - K(i-j)|] \quad -(16)$$

- **Normalized Absolute Error (NAE)**

This measures the distance between original image and reconstructed image

$$NAE = \frac{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}|I(i-j) - K(i-j)|}{\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}|I(i-j)|} \quad -(17)$$

4. Result

The resolution of iris image is enhanced by using two different super resolution algorithms viz. IBP and Median based estimators (Robust). CASIA iris image database is used to analyse the performance of above implemented algorithms. The resolution of the image is 160×120 and resolution after super-resolution is 320×240. Two different iris images are reconstructed using IBP and robust algorithms are shown in fig 1 and fig 2.

Iris 1:

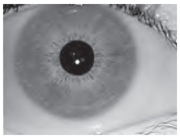
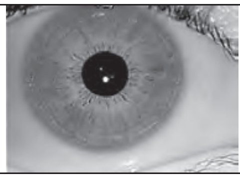
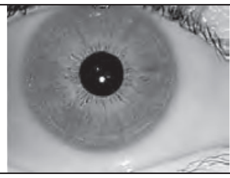
Original	**IBP**	**Robust**
		

Fig.1. Result of Iris Image No.1

The GLCM features of iris image no.1 are as shown in Table 1.

Table 1. Comparison of GLCM features original image and super-resolute image

GLCM Features	Original	IBP	IBP_Error	Robust	Robust_Error
Autocorrelation	21.772	21.821	-0.049	21.82	-0.048
Contrast	0.426	0.364	0.062	0.363	0.063
Correlation	0.899	0.915	-0.016	0.916	-0.017
Energy	0.136	0.143	-0.007	0.143	-0.007
Entropy	2.411	2.373	0.038	2.372	0.039
Homogeneity	0.87	0.888	-0.018	0.888	-0.018

The IBP_Error is the difference between features of original image and resolution enhanced images using IBP algorithm. Similarly, the Robust_Error is the difference between features of original image and resolution enhanced images using robust algorithm. The image quality measures of reconstructed iris image no.1 is as shown in Table 2.

Table 2. Image quality measures

Quality Measures	IBP	Robust
Mean Square Error	18753.000	18753.000
Peak Signal to Noise Ratio	30.188	30.218
Normalized Correlation	0.004	0.004
Average Difference	126.623	126.623

Maximum Difference	254.635	254.636
Normalized Absolute Error	0.996	0.996

Iris2:

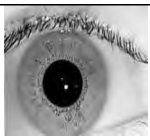
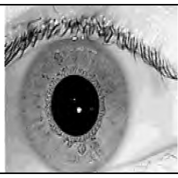
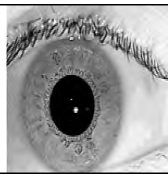
Original	**IBP**	**Robust**
		

Fig.3. Result of Iris image No.2

The GLCM features of iris image no.2 are as shown in Table 2.

Table 3. Comparison of GLCM features original image and super-resolute image

GLCM Features	Original	IBP	IBP_Error	Robust	Robust_Error
Autocorrelation	28.493	28.56	-0.067	28.56	-0.068
Contrast	0.786	0.657	0.129	0.655	0.131
Correlation	0.868	0.895	-0.028	0.896	-0.028
Energy	0.11	0.116	-0.006	0.116	-0.006
Entropy	2.695	2.721	-0.026	2.72	-0.025
Homogeneity	0.818	0.823	-0.005	0.823	-0.005

Image quality measures of iris no.2 is shown in Table 4.

Table 4. Image quality measures

Quality Measures	IBP	Robust
Mean Square Error	26621.000	26621.000
Peak Signal to Noise Ratio	28.667	28.667
Normalized Correlation	0.004	0.004
Average Difference	150.187	150.187
Maximum Difference	254.443	254.441
Normalized Absolute Error	0.996	0.996

Iris image entropy is high as the iris structure is complex in nature. The entropy of reconstructed image using IBP and Robust method is shows the complex structure similar to original iris structure. It shows that IBP and Robust methods do not much affect the iris structure. It has been observed that the energy of reconstructed images is inversely correlated to entropy. The reconstructed image pixels using IBP method have better gray level linear dependence compared to that of using robust. The contrast and homogeneity are inversely correlated in terms of equivalent distribution in the pixel pairs population. The homogeneity is decreasing as increase in contrast.

5. Conclusion and future work

The implementation and performance analyses of IBP and robust super-resolution algorithms are discussed in this paper. The GLCM features of reconstructed images are compared with the features of original image. The features of enhanced iris image closely match with the features of original image. There is a negligible amount of loss of information after enhancing the resolution. The different quality measures are compared and show that the quality of the images remains same after enhancing the resolution by using IBP and robust algorithm. This shows that after enhancing the resolution of iris image, the quality of enhanced image and texture property of the image remains same. In future, the super-resolution of iris images using IBP and robust algorithm can be further extended for enhancing the resolution of normalised iris images captured at a long distance.

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