Novel Super Resolution Algorithm based on LPGPCA & Interpolation for Natural Images

[1]RAMEEZ R BELIM [2]DHARMESH N KHANDHAR

[1]M.E. (E.C.) Student, Dept. of Electronics & Communication Engineering/C.U.Shah College of Engineering and Technology/Wadhwan City/Gujarat/India.

[2] Assistant prof /C.U.Shah College of Engineering and Technology/Wadhwan City/Gujarat/India.

belimrameez@yahoo.com,ddk_2008@yahoo.co.in

Abstract— Image capturing technique has some limitations and due to that we often get low resolution (LR) images. Super Resolution (SR) is a process by which we can generate High Resolution (HR) image from one or more LR images. Here we have implemented algorithm for natural images, so we take some LR images of natural scene which are slightly shifted or rotated due to some limitation of camera or by human mistake.so first we apply Image registration to remove such motion effect & then we apply Image fusion for gathering maximum information from images that are taken from same scene. At last stage we apply image denoising filter to remove noise & then apply Interpolation algorithm to get HR image. This SR algorithm shows much improvement in PSNR & MSE.

Key Words—SR, SIDWTBEF, LPGPCA, Image fusion, Image interpolation.

1 INTRODUCTION

Processing power limitations and channel capabilities are some of the factors because of which images are transmitted at low bit rates and down sampled and due to this reason we get LR compressed images. Computational process known as super resolution (SR) image reconstruction is used to reconstruct HR image from one or more noisy, blurred and down sampled LR images.

For the same scene we can have different images with different looks. Due to capturing technique images are aliased as well as shifted with sub pixel precision [1]. The basic idea for increasing the spatial resolution in SR image reconstruction technique is the availability of several LR images captured from the same scene. Many different methods like nonuniform interpolation, frequency domain approach, regularization and projection onto convex set [2] are available for doing Super Resolution.

In this paper we have taken set of low resolution images of same scene which are shifted & noisy.so first we remove this shift of images & doing Image fusion of this images to get maximum detail of actual image. In next stage we applied image denoising filter to remove the noise from given image & last we apply Interpolation algorithm to get Super resolution (SR) image.finaly we compare with different images in terms of PSNR & MSE.

2 IMAGE REGISTRATION

For doing super resolution, first we need to align LR images and for that we have to do image registration. We can align two or more images of the same scene using registration (Images are taken from different viewpoints or taken at different times) [3]. From available LR images, we consider one image as reference image (base image) to which we can compare other input images. Main goal of registration is to do alignment of input images with the reference image by applying a spatial transformation.

We have considered three shifted images so our first task is to estimate shift between these images in both x and y coordinates. For shift estimation (here we have not consider rotation in images), we have used A Frequency Domain Approach to Registration presented in [4] by Patrick Vandewalle. In Fourier domain, shift between images can be expressed as

$$F2(x) = e^{j2\Pi x T \Delta s} F1(x) \qquad (1)$$

So here we have to find the value of Δs.we can understand this by below steps.

Step 1: Make input images circularly symmetric.

Step 2: Compute Fourier transform of all LR images.

Step 3: Consider one image as reference image.

Step 4: Compute phase difference between reference image and other images.

Step 5: For all frequencies, write linear equation with unknown slope s.

Step 6: Find shift parameter s.

3 IMAGE FUSION

Most exposure fusion methods are easy to be influenced by the location of object in the image. However, when capturing the source images, slight shift in the camera's position will yield blurry or double images. In order to solve the problem, a method called SIDWTBEF (shift-invariant discrete wavelet transform based exposure fusion) is proposed [5], which is based on shift-invariant discrete wavelet transform (SIDWT). It is more robust to images those have slight shift. On the other hand, in this method, we present a novel way to get the chrominance information of the scene, and the saturation of the fused image can be adjusted using one user-controlled parameter. The luminance images sequence of the source images are decomposed by SIDWT into sub- images with a certain level scale. In the transform domain, different fusion rules are used for the high-pass sub-images and the low-pass sub-images combination respectively. In the end, in order to reduce the inconsistencies induced by the fusion rule after applying the inverse transform of SIDWT, an enhancement operator is proposed. Experiments show that SIDWTBEF can give comparative results compared to other shift dependent exposure fusion methods.

In the image fusion research field, the discrete wavelet transform (DWT) based fusion method is proposed to decompose an image into multi-scale edge representation, which is based on the fact that the human vision system (HVS) is primarily sensitive to local contrast change [6]. However, DWT is a shift variant signal representation, which results in a shift dependent fusion method.

We know that discrete wavelet transform (DWT) can be implemented with filter- banks [7]. For image processing application, using a set of 1D low-pass and high-pass filter coefficients, and filters are applied separately on rows and columns can obtain a 2D transformation. Details can be described as follow. Considering an image denoted as I of size N × N, firstly, a low-pass filter H0(z) and a high-pass H1(z) are applied to the rows of I. It creates two images which respectively contain low and high frequencies of I. Secondly, the rows of the two images are subsampled by a factor of 2. It creates two (N/2) × N images. Then the filters are reapplied along the columns, followed by decimation by a factor of 2. Finally, at the output there is four subband images of size (N/2) × (N/2) labelled LL, LH, HL and HH. The operation is recursively repeated on the LL band for more decomposition levels.

When the full decomposition is performed, containing all the DWT coefficients in a tree is got. If the size of image is N × N, the tree contains N2 circular translates. The final step is to find the best basis for decomposition, which is the particular path in the tree which minimizes a cost. The cost is calculated by computing the entropy of each subbands and the path with the minimal entropy is preserved. This best basis corresponds to a translation of vector t1 of the image I. If the input image is a translation of I by a vector t2, the best basis will correspond to a translation of vector t, with t = t1 − t2. The best basis is the same for every shift of the input image.

4 IMAGE DENOISING FILTER

Noise will be inevitably introduced in the image acquisition process and denoising is an essential step to improve the image quality. As a primary low-level image processing procedure, noise removal has been extensively studied and many denoising schemes have been proposed, from the earlier smoothing filters and frequency domain denoising methods to the lately developed wavelet , curvelet and ridgelet based methods, sparse representation and K-SVD methods, shape-adaptive transform, bilateral filtering, non-local mean based methods and non-local collaborative filtering. With the rapid development of modern digital imaging devices and their increasingly wide applications in our daily life, there are increasing requirements of new denoising algorithms for higher image quality.

This is very efficient image denoising method by using principal component analysis (PCA) with local pixel grouping (LPG)[8]. For a better preservation of image local structures, a pixel and its nearest neighbours are modelled as a vector variable, whose training samples are selected from the local window by using block matching based LPG. Such an LPG procedure guarantees that only the sample blocks with similar contents are used in the local statistics calculation for PCA transform estimation, so that the image local features can be well preserved after coefficient shrinkage in the PCA domain to remove the noise. The LPG-PCA denoising procedure is iterated one more time to further improve the denoising performance, and the noise level is adaptively adjusted in the second stage. Experimental results on benchmark test images demonstrate that the LPG-PCA method achieves very competitive denoising performance, especially in image fine structure preservation, compared with state-of-the-art denoising algorithms.

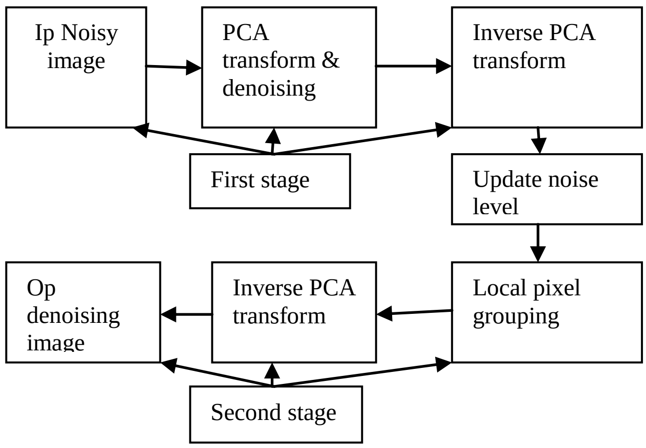

FIGURE 1 Flowchart of the proposed two-stage LPG-PCA denoising scheme.

This is the general block diagram of efficient PCA-based denoising method with local pixel grouping (LPG). PCA is a classical de-correlation technique in statistical signal processing and it is pervasively used in pattern recognition and dimensionality reduction, etc. By transforming the original dataset into PCA domain and preserving only the several most significant principal components, the noise and trivial information can be removed. In [9], a PCA-based scheme was proposed for image denoising by using a moving window to calculate the local statistics, from which the local PCA transformation matrix was estimated. However, this scheme applies PCA directly to the noisy image without data selection and many noise residual and visual artifacts will appear in the denoised outputs.

In the proposed LPG-PCA, there is model of pixel and its nearest neighbors as a vector variable. The training samples of this variable are selected by grouping the pixels with similar local spatial structures to the underlying one in the local window. With such an LPG procedure, the local statistics of the variables can be accurately computed so that the image edge structures can be well preserved after shrinkage in the PCA domain for noise removal.

As shown in Fig. 1, the proposed LPG-PCA algorithm has two stages. The first stage yields an initial estimation of the image by removing most of the noise and the second stage will further refine the output of the first stage. The two stages have the same procedures except for the parameter of noise level. Since the noise is significantly reduced in the first stage, the LPG accuracy will be much improved in the second stage so that the final denoising result is visually much better. Compared with WT that uses a fixed basis function to decompose the image, the proposed LPG-PCA method is a spatially adaptive image representation so that it can better characterize the image local structures. Compared with NLM and the BM3D methods, the proposed LPG-PCA method can use a relatively small local window to group the similar pixels for PCA training, yet it yields competitive results with state-of-the-art BM3D algorithm.

4 IMAGE INTERPOLATION

In interpolation method main issue is to find out information of missing pixels from neighboring pixels as shown in figure.

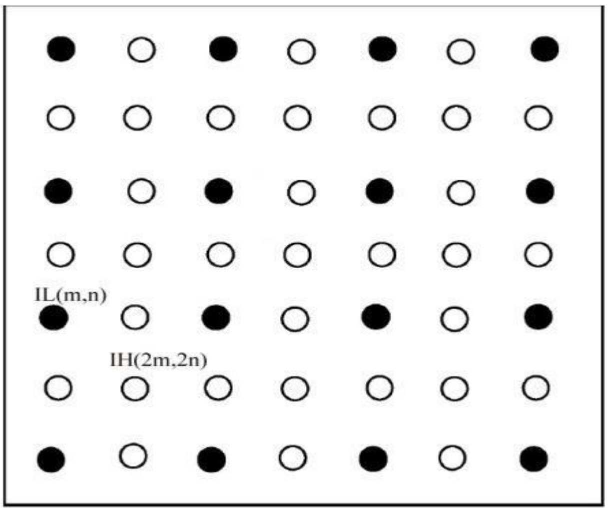

Fig 2 Interpolation Image Structure

Interpolation method for HR image reconstruction suffers from aliasing problem if signal of LR image is down sampled and exceeds Nyquist sampling limit. In spatial locations our human visual system is very sensitive to the edges in image so it is important to suppress interpolation artifacts at the same time maintaining the sharpness and geometry of edges.

For interpolation process edge direction is very important and that’s why we have use An Edge-Guided Image Interpolation Algorithm via Directional Filtering and Data Fusion presented in [10]

Here we have use wavelet based Interpolation method presented in [11] also to do super resolution. For edge information they have partition pixels into two directional and orthogonal subsets. Directional interpolation is made for each Subset and two interpolated values are fused. Algorithm presented in work for gray scale images only so we have done some modification so that it will work for RGB images [12]. As shown below, we have stored each R, G and B components of one image into three different images of two dimensions (same as gray scale image) and give that as a input to original algorithm. Finally we have merged all three output arrays into single RGB image.

```
for i=1:m
  for j=1:n
  R(i,j)=Input(i,j,1);
  G(i,j)=Input(i,j,2);
  B(i,j)=Input(i,j,3);
  end
end

for i=1: (2*m)
  for j=1: (2*n)
  RGB(i,j,1)=Output(i,j);

  end
end      %same way RGB(i,j,2)and RGB(i,j,3)is achieved
```

5 PROPOSED SUPER RESOLUTION ALGORITHM

Here we have presented our proposed algorithm.

1. Take sets of low resolution and noisy images.
2. Apply image registration to remove misalignment
3. Fused all images using the fusion method explained and Get a single image.
4. Apply LPG-PCA based denoising filter
5. Get super resolution image by applying interpolation Method explained in above section.

6 Evaluation Methodologies

Quality measures are computed with known ground truth data:

MSE

The Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR) is the two error metrics used to compare Image compression quality. The MSE represents the Cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error. The lower the value of MSE, the lower the error.

$$MSE = \frac{\sum_{M,N}[I_1(M.N) - I_2(M.N)]^2}{M * N}$$

PSNR

To compute the PSNR, the block first calculates the Mean-squared error using the following equation:In the previous equation *M* and *N* are the number of Rows and columns in the input images, respectively.Then the block computes the PSNR using the following equation:

$$PSNR = 10 \log_{10} \frac{R^2}{MSE}$$

R= size of the image.

6 RESULTS & OBSERVATION

House (256×256)

output (512×512)

Tower (256×256)

output (512×512)

Observation table

Image	PSNR(dB)	MSE
House	**35.82**	**17.01**
Tower	**36.77**	**13.65**

7 CONCLUSION & FUTURE SCOPE

SR image reconstruction is very important in many practical applications. We have taken LPG-PCA based denoising method as very efficient output of image & also fast, require less memory Interpolation method that we have taken is also gives good result as it works on edges as well. Our algorithm is tested on only natural images & gives sufficient results. So, in our future studies, we would like to make this algorithm faster for practical use and want to use different images and interpolation methods.

8 REFERENCES

[1] S. Chaudhuri, Ed., Super-Resolution Imaging. Norwell, MA: Kluwer, 2001.

[2] S. C. Park, M. K. Park, and M. G. Kang, “Super-resolution image reconstruction: A technical review,” IEEE Signal Processing Mag., vol. 20, pp. 21–36, May 2003.

[3] E.D. Castro, C. Morandi, “Registration of translated and rotated images using finite Fourier transform” , IEEE Transactions on Pattern Analysis and Machine Intelligence 700–703,1987.

[4] Patrick Vandewalle, Sabine Susstrunk, Martin Vetterli,” A Frequency Domain Approach to Registration of Aliased Images with Application To Super-resolution”, Hindawi Publishing Corporation, EURASIP Journal on Applied Signal Processing, Volume 2006, Article ID 71459, Pages 1–14.

[5] Jinhua wang, de xu, congyan lang and bing li, “Exposure Fusion Based On Shift-Invariant Discrete Wavelet Transform”, journal of information Science and engineering 27, 197-211 (2011)

[6] G. Piella, “A general framework for multi-resolution image fusion: from Pixels to regions,” Information Fusion, Vol. 4, 2003, pp. 259-280.

[7] O. Rockinger, “Image sequence fusion using a shift-invariant wavelet Transform,” in Proceedings of IEEE International Conference on Image Processing, Vol. 3, 1997, pp.288-291.

[8] Lei Zhang, Weisheng Dong, David Zhang, Guangming Shi, “Two-stage image denoising by principal component analysis with local pixel grouping”, Pattern Recognition 43 (2010) 1531–1549

[9] D.D. Muresan, T.W. Parks, Adaptive principal components and image denoising, in: Proceedings of the 2003 International Conference on Image Processing, 14–17 September, vol. 1, 2003, pp. I101–I104.

[10] Lei Zhang, Xiaolin Wu, “An Edge-Guided Image Interpolation Algorithm via Directional Filtering and Data Fusion”, IEEE Transactions on image processing, vol. 15, no. 8, august 2006.

[11] Ping-Sing Tsai, Tinku Acharya," Image Up-Sampling Using Discrete Wavelet Transform", 9th JCIS 2006, 8 to 11 October 2006.
[12] Sapan Naik, Viral Borisagar, "A novel Super Resolution Algorithm Using Interpolation and LWT Based Denoising Method",International Journal of Image Processing (IJIP), Volume (6):Issue (4): 2012

