International Journal of Advanced Research in Engineering and Technology (IJARET)
Volume 10, Issue 5, September-October 2019, pp. 181-187. Article ID: IJARET_10_05_019
Available online at http://www.iaeme.com/IJARET/issues.asp?JType=IJARET&VType=10&IType=5
ISSN Print: 0976-6480 and ISSN Online: 0976-6499

DIGITAL IMAGE RESOLUTION ENHANCEMENT SCHEME BY EMPLOYING A+ AND NLM FILTER

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ABSTRACT

Resolution enhancement of digital images is one of the active research areas of all time. Images with better quality help in improving the performance of the image analytic systems with better accuracy rates. This article presents a digital image resolution enhancement system by employing A+ and Non-Local Means (NLM) filter. The A+ technique performs well with minimal storage and computational overhead, while increasing the resolution. Finally, NLM filter is applied to refine the resolution enhanced image and the performance of the proposed approach is tested in terms of PSNR and SSIM. The performance of the proposed approach is better, when compared to the existing approaches.

Keywords: Image resolution, resolution enhancement, A+ technique, NLM filter

Cite this Article: T. C. Subbu Lakshmi and Dr. I. Jeena Jacob, Digital Image Resolution Enhancement Scheme by Employing A+ and NLM Filter, *International Journal of Advanced Research in Engineering and Technology (IJARET)*, 10 (5), 2019, pp 181-187.
http://www.iaeme.com/IJARET/issues.asp?JType=IJARET&VType=10&IType=5

1. INTRODUCTION

Digital images are widely applicable in numerous real-time domains such as healthcare, remote sensing and surveillance-based applications [1-4]. The intelligent and decisive image processing-based applications demand the images in high quality. The High Resolution (HR) images render clear-cut information, which paves way for effective image analysis. Hence, the HR images are highly suitable for medical diagnostic systems, remote sensing and tracking based applications. Image resolution enhancement is an active and evergreen research area these days, which presents numerous research solutions.

The image resolution can be improvised by several means and some of the standard ways are to enhance the spatial resolution by minimizing the pixel size. The second way is to maximize the chip size such that the capacitance is improved. However, both the mentioned techniques are expensive and complex to achieve. The third approach improves the resolution of the images by incorporating signal processing approach that considers several images with low resolution for framing the high-resolution image [5]. This approach is considered to be effective than the other two approaches, owing to its simplicity and efficiency.

Recognizing the potential of the resolution enhancement of digital images with the help of signal processing approach, this article employs learning based approach by sparse representation. The sparse representation-based technique builds the dictionaries by means of dictionary learning process. This work utilizes the sparse representations and the trained dictionaries of Low Resolution (LR) images. The learning-based image resolution techniques are promising, as they are based on training datasets and the consideration of relationship between the HR and LR images.

The dictionary learning based resolution enhancement provides minimal computational complexity. However, the dictionary building process ends up in computational complexity. Hence, this work utilizes Adjusted Anchored Neighborhood Regression (A+) technique [19], which does not utilize dictionaries but computes the regressors in the training process. The proposed approach employs fast Non-Local Means (NLM) filter [6] for achieving the research goal. The contributions of this work are as follows.

- The proposed image resolution enhancement approach involves minimal computational complexity.
- The formation of dictionaries is overthrown and the regressors are employed in A+ approach, which brings in simplicity and time efficiency.
- The utilization of NLM manages the image edge artefacts and reduces the time complexity of the algorithm as well.
- The proposed approach shows better performance in terms of Peak Signal to Noise Ratio (PSNR), Structural Similarity index (SSIM).

The remainder of the paper is organized as follows. Section 2 reviews the related literature with respect to the resolution enhancement of digital images. Section 3 presents the proposed resolution enhancement approach and the performance of the proposed approach is evaluated in section 4. The conclusions of the paper are presented in section 5.

2. LITERATURE REVIEW

This section studies and discusses about the related works with respect to image resolution enhancement.

A single-image super-resolution scheme based on sparse signal recovery is presented in [7]. This work performs sparse representation of all the patches of low-resolution images and the high-resolution image is returned as output by utilizing the coefficients. The similarity of the low and resolution image patches is computed by training both the low and high resolution image patch dictionaries. Finally, a high-resolution image patch is generated through the sparse representation of the low-resolution image patch.

A single image scales up by means of sparse representation is proposed in [8], which aims to restore the original image from the corrupted image. This work is based on the image super-resolution through sparse representation presented in [9, 10] meant for regularization. Several improvements are made to minimize the computational complexity and by employing different training approaches.

A locally regularized anchored neighborhood regression is proposed in [11] to achieve super resolution. This work is meant to learn the mapping functions between the LR and HR images with the help of a dictionary of HR and LR samples. This work presents a Locally regularized Anchored Neighborhood Regression (LANR) that utilizes the locality constrained regression rather than the ridge regression in ANR. This work claims itself to be more flexible and proves better PSNR rates.

The recent techniques, applications and future of image super-resolution are discussed in [12]. The review of super resolution and the contributions of the techniques are presented. Additionally, details about reconstruction models, parameter selection techniques, optimization algorithms and acceleration strategies are outlined. In [13], a real-time single image and video super resolution using an efficient sub-pixel Convolutional Neural Network (CNN) is presented. This work employs CNN architecture for extracting the feature maps in the LR space. Additionally, an efficient sub-pixel convolution layer for learning an array of upscaling filters to upscale the LR image to HR image.

In [14], a deep Laplacian pyramid networks are utilized to achieve faster and an accurate super resolution. The Laplacian pyramid super-resolution networks reconstruct the sub-band residuals of the HR images. In every pyramid level, the coarse resolution feature maps are passed as input and the high frequency residuals are predicted. This is followed by the process of up sampling the transposed convolutions. This work trains the network with deep supervision by Charbonnier loss function for achieving better quality reconstruction. In [15], a super resolution reconstruction of diffusion parameters from diffusion-weighted images with different slice orientations. This approach employs a diffusion model for reconstructing the high-resolution diffusion parameters by means of low-resolution diffusion-weighted images.

In [16], a deeply recursive convolutional network is proposed for image super resolution with 16 recursions. The recursion depth is increased without introducing additional parameters for convolutions. A technique based on deep convolutional networks to attain image super-resolution is presented in [17]. The CNN utilized by this work is lightweight with better speed and this work optimizes all the layers involved. A technique for super resolution reconstruction based on multilevel main structure and detail boosting is presented in [18]. This work extracts the multilevel texture information through difference process and the main structure is segregated from the texture detail respectively. The missing high frequency details are compensated with the help of detail-boosting function. Finally, the multilevel main structure and the texture information are combined together to attain high resolution image.

Motivated by the above presented works, this work aims to present an image resolution enhancement approach based on Adjusted A+ in association with NLM filter. The proposed approach is described in the following section.

3. PROPOSED IMAGE RESOLUTION ENHANCEMENT APPROACH BASED ON A+ AND NLM FILTER

Due to the advancements of digital imaging technology, most of the real-time applications make use of digital images for analysis and decision making. Hence, the accuracy of the applications relies on the effectiveness of the image analytic techniques. One of the main ways to boost up the accuracy rate of the image processing or analytic system is the resolution enhancement technique. This article proposes an approach to enhance the image resolution by applying A+ and NLM filter techniques.

The A+ technique assumes that the LR image is linearly represented by the k nearest sample neighbors of the nearby LR atom. Similarly, the computed HR image patch is assumed to be represented by the k nearest HR sample neighbors with the representation coefficients. The k-nearest neighbors are selected with respect to the LR sample neighbors and not the HR sample neighbors. As the similarity of the patches is considered, the HR sample patches could be incorrectly matched with the large representation coefficients. This issue is addressed by the A+ technique by calculating the regressors from the LR and HR patches in place of the dictionary learning as in [11,20]. Additionally, the A+ technique computes the weights by means of HR similarities, whereas the LANR [11,20] computes weights through the LR relationship.

The A+ approach [19] is based on three significant steps and they are dictionary learning, projection matrix formulation, resolution enhancement. All these steps are described as follows.

3.1. Dictionary Learning

Initially, the training data is formed by the LR image patches represented by $P = [lp_1, lp_2, lp_3, \dots, lp_M] \in \mathbb{C}k_l \times M$. The HR sample patches of the mentioned LR image patches are represented by $Q = [hp_1, hp_2, hp_3, \dots, hp_M] \in \mathbb{C}k_h \times M$, where M denotes the count of training entities. The dictionary of LR image patches is obtained by $Kl = [kl_1, kl_2, \dots kl_N] \in \mathbb{C}k_l \times N$ and the HR dictionary is represented by $Kh = [kh_1, kh_2, \dots kh_N] \in \mathbb{C}k_h \times N$ for the training samples, which is done by the sparse method discussed by [21]. The dictionary atoms are denoted by the term anchor points. The projection matrix formation is discussed in the following section.

3.2. Projection Matrix Formation

Every anchor point (kl_j) in the dictionary is considered for the automated detection of the nearby LR neighboring points $Nl_j = \left[lp_{j,1}, lp_{j,2}, \dots, lp_{j,KN}\right]$ for P and the HR neighbours are represented by $Nh_j = \left[hp_{j,1}, hp_{j,2}, \dots, hp_{j,KN}\right]$ for Q. The projection matrix is then detected with respect to the anchor point kl_j, which is as follows.

$$PM_j = Nh_j \left[\left(Nl_j\right)^T Nl_j + \alpha \mathrm{I}\right]^{-1} \left(Nl_j\right)^T \tag{1}$$

In the above equation, $\alpha > 0$ and is a constant value.

3.3. Resolution Enhancement

When a LR image patch (lp) is passed, then the closest neighbour point kl_j in Kl is detected and the projection matrix PM_j is computed. The approximate resolution enhanced image is computed by $\widehat{PM}_h = PM_j p_l$. By this way, the projection matrices are computed and saved in the local database, which makes the process simple and reduces the computational complexity as well. As mentioned earlier, the likeness of the HR image patches is regulated through weights with respect to every representation coefficient and the ridge regression problem is stated as follows. Let the representation coefficients are denoted by $\widehat{\beta_J} = \left(\hat{\beta}_{j,1}, \dots, \hat{\beta}_{j,KN}\right)^T$. This work considers that the approximate HR patches of image are represented in linear fashion by the HR samples in Nh_j. The representation coefficients are modified with the weighted coefficients $\omega_j = \left(\omega_{j,1}, \dots, \omega_{j,KN}\right)^T = WT_j \widehat{\beta_J}$, in contrary to the LANR. The resolution enhanced image patches are computed by the following equation.

$$\widehat{PM}h_{wt} = \sum_{m=1}^{KN} \omega_{j,m} PMh_{j,m} = Nh_j \omega_j \tag{2}$$

This equation can be written as

$$\widehat{PM}h_{wt} = \left(Nh_j WT_j\right) \left[\left(Nl_j WT_j\right)^T \left(Nl_j WT_j\right) + \alpha \mathrm{I}\right]^{-1} \left(Nl_j WT_j\right)^T pml \tag{3}$$

The similarity index is then found out between the HR image patch $PMh_{j,m}$ and the cluster centre PMh_{jc} in Nh_j by the following equation.

$$SIh_{j,m} = \exp\left(-\frac{\left\|PMh_{j,m} - PMh_{jc}\right\|^2}{\sigma_j}\right);\ m = 1,2,3, \dots, KN \tag{4}$$

In the above equation, σ_j is the bandwidth attribute and the similarity of the HR patches with weights is done by

$$wt_{j,m} = \frac{SIh_{j,m}}{mv(SIh_j)}; m = 1,2,3, KN \tag{5}$$

$mv(SIh_j)$ represents the mean value of $SIh_{j,m}$. Hence, the weights are considered for resolution enhancement and the result attained is refined with the help of NLM filter. This idea improves the image quality and the performance of the proposed work is evaluated in the following section.

4. RESULTS AND DISCUSSION

The performance of the proposed approach is implemented in Matlab version 2016a on a standalone computer with 8 GB RAM. The performance of the proposed approach is tested in terms of PSNR and SSIM, while the results are compared with the existing approaches such as sparse representation [7], scale-up [8], LANR [11], LANR+NLM [20]. The performance of the work is tested over the datasets set5 and set14 with 5 and 14 images respectively [10]. The scaling factors are varied as 2, 3 and 4. The results are presented as follows.

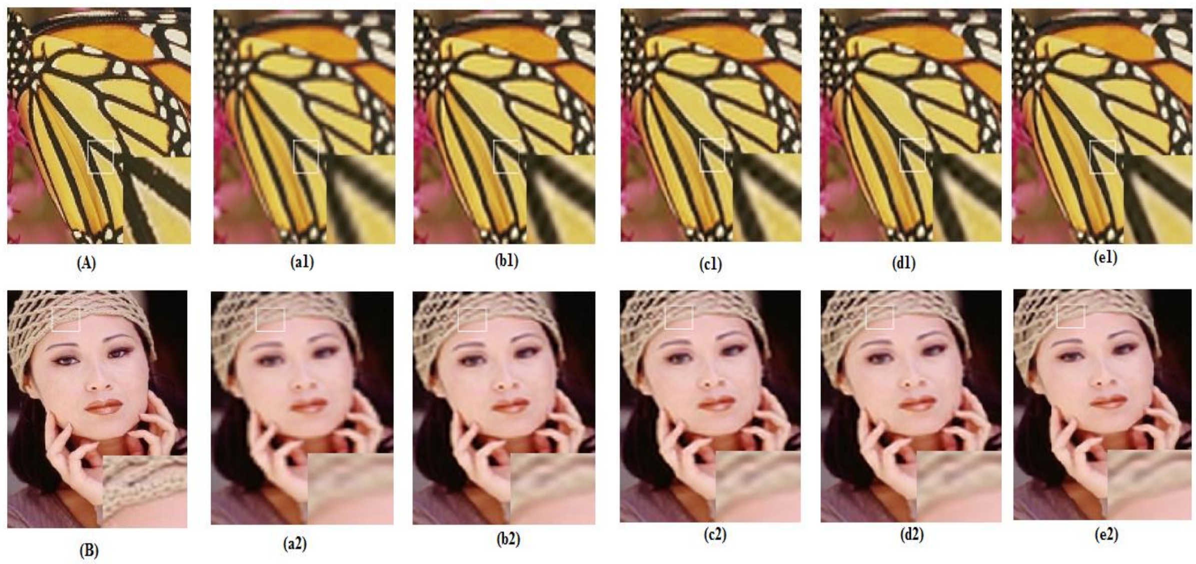

Figure 1 (A, B) Original HR images, (a1, a2) sparse representation [7], (b1, b2) scale-up [8], (c1,c2) LANR [11], (d1,d2) LANR+NLM [20], (e1,e2) proposed work

The visual results prove the efficiency of the work with better details and the results attained by the proposed work are tabulated as follows.

Table 1 Performance comparison

DS	SF	[7]		[8]		[11]		[20]		Proposed	
		PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Set 5	2	32.6	0.934	34.8	0.946	35.93	0.951	36.42	0.954	36.64	0.956
	3	29.83	0.871	32.7	0.894	32.7	0.899	32.41	0.916	32.81	0.919
	4	27.91	0.824	30.4	0.851	29.7	0.904	30.23	0.871	30.41	0.873
Set 14	2	30.21	0.864	31.87	0.886	31.94	0.841	32.14	0.912	32.18	0.921
	3	28.61	0.774	29.87	0.804	29.41	0.795	30.17	0.826	30.34	0.828
	4	25.98	0.698	27.69	0.742	30.27	0.771	26.98	0.769	27.12	0.773

From the experimental analysis, it is evident that the proposed approach proves better performance than the existing approaches. The work presented in [20] gives tough competition to the proposed approach, yet the proposed work proves better performance in terms of PSNR and SSIM. Both the visual and the numerical results prove the performance of the proposed work.

5. CONCLUSION

This article presents an approach to enhance the resolution of the digital images by employing A+ and NLM filter. This work involves three major phases and they are dictionary learning, projection matrix formation and resolution enhancement. Finally, the attained results are enhanced further by NLM filter. This idea improves the quality of the image, while costing minimal memory and computational overhead. The performance of the proposed approach is tested in terms of PSNR and SSIM. The proposed work performs better than the existing approaches. In future, the performance of the work can further be increased by focusing more on the PSNR and by reducing the time complexity.

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