IJCSC 0973-7391 Volume 7 • Number 2 March 2016 - Sept 2016 pp. 115-119 available online at www.csjournalss.com

Wavelet Domain Interpolation with Edge Extraction and Sparse Representation generating super resolution image.

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Abstract: In this paper, it is proposed a new image resolution enhancement algorithm based on discrete wavelet transform (DWT), lifting wavelet transform (LWT) and sparse recovery of the input image. A single low resolution (LR) is decomposed into different sub bands using two operators DWT and LWT. In parallel, the LR image is subjected to a sparse representation interpolation. The higher frequency sub-bands in addition to the sparse interpolated LR image are combined to give a high resolution (HR) image using inverse discrete wavelet transform (IDWT). The qualitative and quantitative analysis of this method shows prominence over the conventional and various state-of-the art super resolution (SR) techniques.

Keywords: Edge extraction, interpolation, sparse mixing estimators, super resolution (SR), wavelet domain.

I. INTRODUCTION

With the recent advancement of image and video imaging there is a constant need of getting a better resolution image. One promising approach is to use signal processing techniques on low resolution (LR) image(s) to achieve a HR image(s). This technique of generating a HR from a single or a multi LR images is referred as super resolution (SR). This is categorized into two form, one with input from multi source LR images with sub-pixel shift such as depicted in [1, 2] and other with single LR image [3, 4, 5]. The work on the former has been around for a long time. The multi-frame SR suffers from the fact that it requires multiple LR input image with sub-pixel shift leading to poor image registration. This makes it an ill-posed problem, thus a regularization term is often a need but the type of prior term for regularization is an issue. These have been carefully considered in the single image version of the SR techniques. The single image super resolution techniques are further categorized broadly into interpolation techniques, machine learning techniques and wavelet based techniques. The linear interpolation techniques like bicubic, bilinear suffer from the fact that higher frequency details are lost when magnification factor is increased leading to deprivation in edge information. Li and Orchard [6] worked on this problem and proposed a solution based on edge directed interpolation. The basic idea lies in working on geometric duality between the estimated covariance coefficients between the low resolution image and the interpolated version of the image. In spite of appreciable performance, this method of covariance-based adaptation interpolation introduces complexity. Zhang and Wu [7] further worked on enhancing the edge information by proposing a new edge guided nonlinear interpolation technique which uses directional filtering and data fusion. However owing to the complexity in estimation and computation, the research on image enhancement now focused on newer techniques like discussed below. The second category is based on machine learning which uses a "learning step" between a HR images (like of face, fingerprint, wall etc.) and their LR counterparts. This learned knowledge is then incorporated in a priori term for the reconstruction. Notable work done by Mallat and Yu [8] focuses on adaptive estimators obtained by mixing a family of linear inverse estimators, derived from different priors on the signal regularity. The path-breaking work done by yang et al [5] is based on sparse-land local model which assumes that each patch from the LR image can be represented using a linear combinations from a dictionary. Simply, each patch is considered to be generated by multiplying a dictionary by sparse vector coefficients. However for a higher magnification factor, the results are not satisfactory. In parallel, many techniques using wavelets decomposition operators for single image scale up problem (i.e. single image super resolution) have been around the corner for the recent times. This third category is based on enhancement using wavelet decomposition [9, 10, 11 and 12]. Generally in this method, the input image is decomposed into structurally correlated sub-images which allow exploiting the self-similarities between local neighbouring regions. In [12] the input image is first decomposed into subbands. Then the input image and the high-frequency subbands are both interpolated. The results of a stationary wavelet transform of the high-frequency subbands are used to improve the interpolated subbands. The super-resolved HR output is generated by combining all of these subbands using an inverse discrete wavelet transform (IDWT)

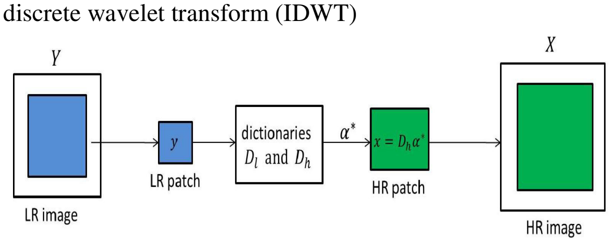

Fig.1 Flow chart of sparse representation

However the image still persists blurriness and artifacts when the magnification factor is increased to a level of four.

A new method recently developed by Roman and Ponomaryov in [13] suggest using a novel edge preservation concept for sharper image using DWT and sparse mixing estimation of the input image. This method focuses on the concept taken up by the above authors but with modifications. In this proposed method, it have not used the redundant edge preservation step rather used a lifting scheme. The lifting scheme allows one to custom-design the filters, needed in the transform algorithms, to the situation at hand. The lifting scheme builds a new wavelet, with improved properties, by adding a new basis function [14].This insures a fast in-place calculation of the wavelet transform, i.e. an implementation that does not require auxiliary memory. Another modification is in using the concept of sparse representation, developed by yang et al [5]. The proposed method is compared with the conventional and state-of-the-art methods. The qualitative and quantitative assessment shows the prominence of this method over the above mentioned methods.

II. METHODOLOGY

A. Signal Recovery based on Sparse Representation

In an image enhancement problem, given a low resolution image and it need to find its higher resolution version. This recovery is generally an ill-posed problem because there can be infinitely many solutions for a LR image to be considered a down-sampled version of its higher resolution, so a regularizer term is often required. For proposed case consider a sparse coefficient to be a regularizer. For this, suppose there exist an over-complete dictionary $D \in R^{n\times K}$ having K element. Let a signal $x \in R^{n}$ be represented as a sparse Linear combination with respect to D. The signal x can then be represented as here $\alpha \in R^{K}$ is any vector with less (<< n) nonzero entries. Now, since the low resolution image is considered to be a blurred and decimated version of a high resolution image LR patch, y, can be written as a decimated version of high resolution patch. Mathematically,

$$y = Mx = MD\alpha, \qquad (1)$$

where $M \in R^{k\times n}$ with $k < n$ is a projection matrix which controls the decimation and blurriness factor. The equation $x = D\alpha$ is an underdetermined for the obscure coefficients α given the dictionary D be an over-complete one [5]. The equation $y = MD\alpha$ is then even more Un-determined. Under mild conditions the sparsest solution α^* to the above equation will be unique. Further if D satisfies a near-isometric condition, then any sparse representation of HR image patch with respect to dictionary D can be recovered for the LR image patch. The sparse recovery process is shown in Figure 1.

Algorithm for Sparse Recovery:

Input: Take low resolution image Y as input along with two training dictionaries D_h and D_l

For 3x3 patch '*p*' of taken in raster scan order with an overlap of one pixel, solve the optimization problem for α

$$\alpha^* = arg\ min \lambda \|\alpha\|_1 + \frac{1}{2}\|D_l \alpha - p\|_2^2$$

Place HR patch, $x=D_h\alpha^*$ in S_o

End

Output: Sparse recovered image S_o

In this case, it uses dictionaries trained by *yang et.al* method.

B. PROPOSED SR-WDIEE-SR TECHNIQUE

In this letter, one level of DWT that applies different wavelet families is used to decompose an input image. DWT separates an image into different subband images, namely, LL, LH, HL, and HH, where last three subbands contain the HF component of the image. The interpolation process should be applied to all subband images. To suppress noise influence, the novel framework applies a denoising procedure by using the NLM technique for the input LR image (see step 1 in Fig. 2). In the proposed SR procedure, the LR image is used as the input data in the sparse representation for the resolution enhancement process in the following way (see step 2a in Fig. 2). The LR image is calculated by using a 1-D interpolation in a given direction θ and then following the computations of the new samples along the oversampled rows, columns, or diagonals. Finally, in this step, the algorithm computes the missing samples along the direction θ from the previously calculated new samples, where the entire sparse process is performed with the Lanczos interpolation (factor α = 2), reconstructing the LL subband.

The differences between the interpolated (factor α = 2) LL subband image and the LR input image are in their HF Components, which is why the intermediate process to correct the estimated HF components applying this difference image has been proposed. As shown in step 2b of the algorithm (see Fig. 1), this difference is performed in HF subbands by interpolating each band via the NNI process (changing the values of pixels in agreement with the closest neighbor value), including additional HF features into the HF images. To preserve more edge information (to obtain a sharper enhanced image), it propose an extraction step of the edges using HF subbands HH, HL, and LH images; next, the edge information is used in HF subbands employing the NNI process (see step 2c in Fig. 1). The edges extracted are calculated as follows [16]:

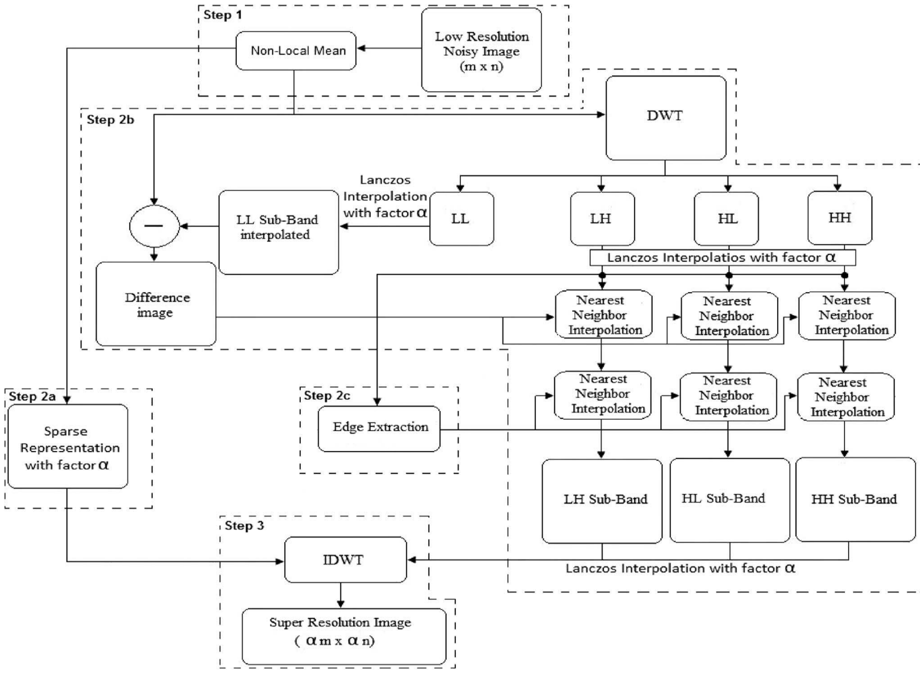

Fig.2 Block diagram of the proposed resolution-enhancement technique.

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$$E = \sqrt{\mathrm{HH}^2 + \mathrm{HL}^2 + \mathrm{LH}^2}. \qquad (2)$$

In the concluding stage, it performs an additional interpolation with the Lanczos interpolation (factor $\alpha = 2$) to reach the required size for the IDWT process (see step 3 in Fig. 2). It is noticed that the intermediate process of adding the difference image and the edge extraction stage, both of which contain the additional HF features, generate a significantly sharper reconstructed SR image. This sharpness is boosted by the fact that the interpolation of the isolated HF components in HH, HL, and LH appears to preserve more HF components than interpolating from the LR image directly.

III. SIMULATION RESULTS AND DISCUSSION

This section reports the results of the statistical simulations and the performance evaluation that is conducted via objective metrics (Peak Signal-to-Noise Ratio, Mean Absolute Error, and Structural Similarity Index Measure) [17]. In addition, a subjective visual comparison of the SR images performed by different algorithms was employed and thus made it possible to evaluate the performance of the analysed techniques in a different manner.

Numerous aerial optical and radar satellite images from [13] and [14], particularly *Aerial-A* and *SAR-B* images of different nature and physical characteristics were studied applying the designed and better existing SR procedures. In simulations, the pixels of the LR image have been obtained by downsampling the original HR image by a factor of 4 in each axis. In the denoising stage, the NLM filter from (2) was applied, the neighbourhood Q was found in the simulation as 5×5 pixels, and the parameter $\delta = 2$ was chosen.

IV. CONCLUSION

In this paper, it have been developed an effective image enhancement technique using concept of sparse recovery and wavelet transformations. The input image is decomposed into different subbands using DWT. Since using DWT decimates an image and loss in high frequency components, so it have been used a second generation wavelet transformer LWT, whose first derivative preserves the edges and second take care of the curves present in the image. Then, the higher frequency components are added up. In parallel, it sparsely recovers the input image with an interpolation factor of two. The three higher subbands and the sparse recovered image are applied to IDWT and finally to a reconstruction based algorithm to give a super resoled image. This method is applied on four well known test images and the experimental results shows prominence.

TABLE I RESULTS OF THE RESOLUTION ENHANCEMENT

SR METHODS	NLM APPLIED				
	SSIM	PSNR	MAE	MSE	RMSE
DB1	0.8962	30.5415	5.7521	57.8529	7.6061
BIO1.3	0.8949	30.4741	5.8047	58.7590	7.6654
DB1	0.8741	34.3937	3.8350	23.8292	4.8815
BIO1.3	0.8716	34.2332	3.9099	24.7262	4.9725
DB1	0.8738	34.4666	3.8037	23.4324	4.8407
BIO1.3	0.8719	34.3655	3.8600	23.9847	4.8974
DB1	0.8864	30.0977	6.2225	64.0775	8.0048
BIO1.3	0.8869	30.0948	6.2217	64.1210	8.0076

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