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Single Image Super-Resolution Based On Second Order Regression and Sparse Representation Model

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ABSTRACT

This paper presents a regression model to generate a High Resolution image from a single Low Resolution image. The local regression based single image Super-Resolution (SR) is done without any external images as training set. The single input image is the only source used to learn the relationship between the Low Resolution (LR) and the High Resolution (HR) images. The local regression model is used in order to derive the relationship between the LR and HR example patches. The mapping between the LR-HR images is estimated by a first order regression model and a second order regression model based on a dictionary. This problem can be regularized by using example priors. The in-place self similar patches within the image is used as priors. The proposed method produces visually good images compared to the other algorithms used for SR. This algorithm works well for input images with diverse texture and the images degraded with noise and blur.

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INTRODUCTION

Super-resolution is one of the most extensively researched topics in image processing. Super-resolution (SR) is the process of estimating a high resolution (HR) image from one or more low resolution (LR) images. The super resolved image offers greater pixel density and more details about the image. Image SR is a necessity in many computer vision, medical imaging and satellite imaging applications. The emergence of high definition displays in the recent years has also created a great demand to super resolve the existing poor quality images.

The SR algorithms generate a HR image based on three main techniques they are: Interpolation based (Freedman, G. and R. Fallal, 2011), Learning based (He, H. and W.-C. Siu, 2011; Yang, J., *et al*., 2013; Timofte, R., *et al*., 2013) and Reconstruction based methods (Fattal, R., 2007; Yang, J., *et al*., 2013; Yang, J., *et al*., 2012). Each of the above method has its own advantage, requirements and prior assumptions. The Interpolation based method uses linear kernel to estimate the pixel values of the HR image thereby producing smooth images with artifacts such as ringing, aliasing and blocking e.g., bi-linear or bi-cubic interpolation technique. The Reconstruction based method solves the SR as an inverse problem. This technique uses multiple LR images to obtain the HR image. Multiple images are obtained for the same scene with sub pixel shift and the HR image is obtained by combining these images. This method uses various smoothening priors in order to obtain the HR image. This is an extremely under-constrained problem. This method incorporates different priors for various images such as gradient profile prior (Fattal, R., 2007), smoothening prior (Dai, S., *et al*., 2009), Sparse and redundant priors etc. This method is better in terms of performance compared to the interpolation based technique. The drawback with this method is that it suffers with visual artifacts for higher magnification factor thereby limiting the applications of this technique. The Learning methods are capable of overcoming the limitations inherent with the reconstruction based methods and interpolation based methods. In the Learning based method the relationship between the LR patches and the corresponding HR patches is predicted by using external training images. This method aims to determine the high frequency details which are not found in the LR image. Challenge involved in the method lies on the selection of the external training image set. Improper selection of the training set results in imprecise details in the resulting HR image. To overcome the imprecise details the self

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learning algorithms (Jing Hu andYupinLuo, 2014; Sundaresh Ram and Jeffrey J. Rodriguez, 2014) have evolved recently. The LR input image is the only source used to estimate the LR-HR relationship in this method. The self learning algorithm does require any external training image set to obtain the LR-HR relationship.

The self learning algorithm uses Local Regression model for image SR. The regression model is used to estimate the relationship between the LR-HR image patches. This method does not require any external training database and the LR input image is the only source used for generating the HR image. The single image SR is based on the concept on self-similarity. Local image patches or structures appear repeatedly in an image with same and different image scales. These local self similar example patches can be used to regularize the image SR rather than an external training database. Compared to the external database, the example patches from the LR image itself is capable of learning the true high frequency contents. For an in-place self similar patch in an upper scale image, a mapping function is used to restrict the corresponding patch in the lower scale image. To the LR image patch a first order approximation of a non linear mapping function is applied and the corresponding HR image patch is obtained. This algorithm extended to handle images contaminated with noise and blur.

In the proposed method of SR using in-place self similar image patch pair based on regression model. Initially a LR-HR patch pair is obtained by separating the LR image and its smoothened version into overlapping patches. With the help these patch pairs a regression model is constructed. The mapping function that determines the LR-HR patch relationship is derived using the regression model. Regression analysis is generally used to estimate the relationship between variables. The relationship between the LR and HR image patch is determined using the local regression model. The first order regression model is used to reconstruct images degraded with noise, whereas it does not work well with blurred images. So the second order regression model is used to reconstruct images degraded with blur. The first order and the second order coefficients of the model are estimated using a dictionary based on sparse representation.

The dictionary is constructed and trained using the LR-HR image pair using sparse signal representation. The dictionary is completely trained by the patches taken from a single image. The higher order regression model coefficients are determined by the dictionary, thereby a mapping function between the LR and HR image is formed. The contribution of this paper can be summarized as follows:

A) Self learning SR algorithm based on local regression.

B) Dictionary training based on sparse representation.

C) Dictionary based regression model coefficients.

The remainder paper is organized as follows, the forthcoming section gives an overview about the Self learning SR methodology, Dictionary construction and training based on sparse representation and learning of Regression model coefficients based on dictionary. Section 3 gives the experimental results and comparison between various algorithms. The conclusion of the paper is given in Section 4.

2 Proposed method:

2.1 Self learning SR algorithm based on Local Regression:

The LR input image is denoted as X_0. HR image is represented as X. The LR image X_0 with sharp areas has an undesirable pixel resolution. The pixel resolution of the output image is r times greater than the input image. Their corresponding low-frequency band is denoted by Y_0 and Y. Sampled image patches of dimension $a \times a$ are denoted as x_0 and x with respective X_0 and X. Similarly for low frequency content y_0 and y are represented for Y_0 and Y. r is a constant scaling factor.

The proposed SR methodology is the modification of the work done by Ram *et al.* (Sundaresh Ram and Jeffrey J. Rodriguez, 2014) and it is shown in Fig.1. The in-place self-similarity based regression model is the improvement of work done by Jing *et al.* (2014). Ram *et al.* (2014) used the first order regression model to reconstruct the HR image. The LR input image is $X_0 \in \mathbb{R}^{K_1 \times K_2}$. In order to obtain low frequency content of that, the image is filter using a Gaussian filter. The filtered image is denoted as $Y_0 \in \mathbb{R}^{K_1 \times K_2}$. Interpolate the LR image X_0 by a factor r to get $Y \in \mathbb{R}^{rK_1 \times rK_2}$, upsampled image. The Low frequency content of output image X_0 is approximated by using image Y. From the knowledge of X_0, Y_0 and Y, the output HR image X is estimated by the use of regression model.

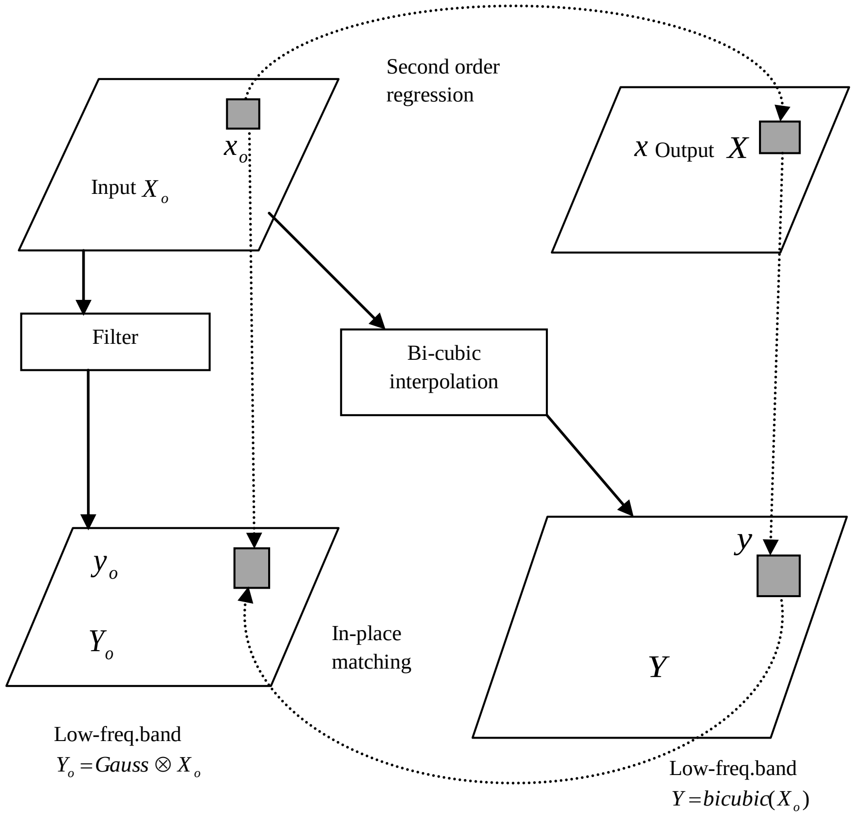

Fig. 1: Image patch based Super-resolution methodology

From the image Y at (i, j) location image patches y are taken. With the help of that corresponding in-place self-similar example patch y_0, corresponding coordinates (i_s, j_s) are taken from Y_0, where $i_s = \left\lfloor i/r + 0.5 \right\rfloor$ and $j_s = \left[j/r + 0.5 \right]$ and similarly the image X_0 is sampled to obtain the image patches x_0, which is the HR version of Y_0.

The local regression model is a statistical process, which gives the relationship between two independent measurements or variables, x_n and y_n using an unspecified regression function, where x_n is the predictor variable and y_n is the response variable.

$$y_n = f(x_n, \varepsilon_n) \tag{1}$$

Where ε_n the estimation error and its value approaches zero under smoothness assumption. The general solution for the regression model is obtained using a N-term Taylor series.

2.1.1 First order Regression Model:

The regression analysis is used to solve the single image SR problem. Local regression is used to find a non-linear mapping function f between LR image and HR image. Learning of mapping function requires good prior and proper regularization. Good prior is obtained from SR methodology. $\{y_0, x_0\}$ is the obtained prior. These are interfaced to form y which is the HR image. The regression model based mapping function expansion is obtained from the inference made by Ram *et al*. (2014). For a continuously differentiable function f the Taylor series is expanded and approximated as,

$$\begin{aligned} x &= f(y) = f(y_0 + y - y_0) \\ &= f(y_0) + \nabla f^T(y_0)(y - y_0) + \mathrm{O}\left\{\|y - y_0\|_2^2\right\} \\ &\approx x_0 + \nabla f^T(y_0)(y - y_0) \end{aligned} \tag{2}$$

Instead of finding non-learning function f, ∇f gradient function is used, because it is easier. ∇f Gradient function is generated using dictionary, constructed with the help of prior pair $\{y_0, x_0\}$. After generating the mapping function, given with any input (LR) patch y, we find its in-place example patch pair $\{y_0, x_0\}$, then to find $\nabla f(y_0)$ with the help of the trained dictionary. Then First-order approximation is used to find HR image patch x. The first order approximation function cannot efficiently handle images degraded with noise.

2.1.2 Second order Regression model:

The mapping function formed using first order regression coefficients is best suited for reconstructing images corrupted with noise, but it cannot handle blurred images. Therefore higher order approximation function is useful in finding the complex non-linear function. The general higher order Regression model is the Taylor series expansion of the mapping function, represented as

$$f(y) = f(y_0) + f'(y_0)(y-y_0) + \frac{1}{2} f''(y_0)(y-y_0)^2 + \ldots + \frac{1}{N!} f^N(y_0)(y-y_0)^N$$

$$= \beta_0 + \beta_1 (y-y_0) + \beta_2 (y-y_0)^2 \qquad (3)$$

Where

$\beta_0 -$ Pixel value

$\beta_1 - \nabla f(y_0)$

$\beta_2 - \nabla^2 f(y_0)$

The coefficients and are determined using a Sparsity based Dictionary. The first order and the second order approximation can be combined to reconstruct images efficiently.

2.2 Dictionary Learningand Regression model coefficients:

The model proposed by Yang *et al*. (2013; Yang, J., *et al*., 2012) is the basis for the determination of the dictionary based mapping function. This dictionary used here is an overcomplete dictionary, denoted as $D_h \in \mathbb{R}^{n \times K}$ in which $n << K$, where K is called atoms. Atoms are also known as sparse coefficient vector, which has got the high frequency content. The dictionary generation is based on the HR image. X is a HR image represented as sparse linear combination of the atoms of D_h, with any patch $x \in \mathbb{R}^n$.

$$x \approx D_h \alpha, \text{With} \|\alpha_0\| << K \qquad (4)$$

For LR image, y patch is obtained with the help of dictionary D_l and with same spare coefficient vector α. α is obtained by co-training D_h and D_l. The dictionary training and determination of α is done with the help of work done by Yang *et al*. (2013)

$$\alpha^* = \min_{\alpha} \|GD_l \alpha - Gy\|_2^2 + \lambda \|\alpha\|_1 \qquad (5)$$

Where G and H are the feature extraction operators. G is the gradient operator used to emphasize high frequency details of an image. H is the Laplacian operator used to find the second order derivative of an image.

$$g_1 = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} \quad g_2 = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix}$$

$$h_1 = \begin{bmatrix} 0 & 0 & 0 \\ +1 & -2 & +1 \\ 0 & 0 & 0 \end{bmatrix} \quad h_2 = \begin{bmatrix} 0 & +1 & 0 \\ 0 & -2 & 0 \\ 0 & +1 & 0 \end{bmatrix}$$

Feature extraction operator G is the concatenation of 2-D filters. λ is the factor which will control sparsity solution vector α^*. To increase texture details non-zero coefficient has to be adapted. But with this noise and artifacts will also get increased. Therefore, based on standard deviation (σ) of the patch, λ takes the form.

$$\lambda = \begin{cases} 0.5 & if \quad \sigma < 15 \\ 0.1 & if \quad 15 \le \sigma \le 25 \\ 0.01 & if \quad \sigma > 25 \end{cases} \qquad (6)$$

Here, σ is mainly used for 8-bit gray-scale image and it can also be adapted for other type of images.

$$\nabla f(y_0) = \beta_1 = GD_h \alpha^* \qquad (7)$$

$$\nabla^2 f(y_0) = \beta_2 = HD_h \alpha^* \qquad (8)$$

Instead of commonly used Gaussian blurring operator we make use of bilateral filter to obtain Y_0 from the given image for training the dictionary. This will suppress the noise and artifacts but enhances the texture. $X_h = \{x_{0_1}, x_{0_2}, \ldots, x_{0_m}\}$ HR patch vector, LR patch vector $Y_l = \{y_{0_1}, y_{0_2}, \ldots, y_{0_m}\}$ and residue patch vector $E = \{x_{0_1} - y_{0_1}, x_{0_2} - y_{0_2}, \ldots, x_{0_m} - y_{0_m}\}$ is used in the dictionary training process.

Concatenated dictionary is defined by,

$$C = \begin{bmatrix} D_h \\ D_l \end{bmatrix} \quad (9)$$

The learned dictionary pairs are the compact representation of the LR and HR image patch pairs.

The coupled dictionaries are used to derive the regression models. The block diagram of the proposed SR methodology is shown in Fig.2.

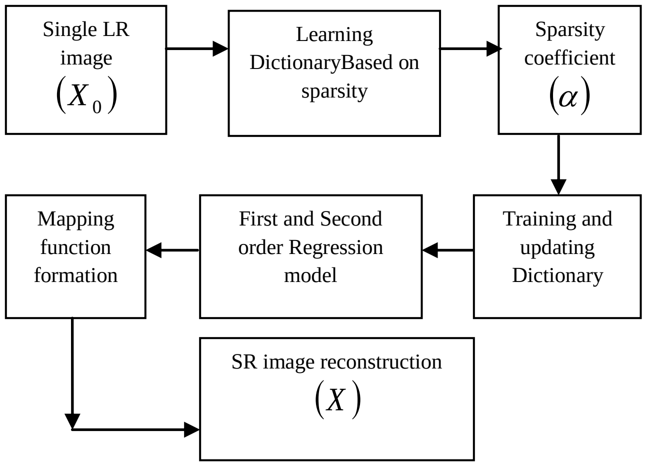

Fig. 2: Block diagram of the proposed work

Simulation Results:

The proposed algorithm for single image SR is tested using various test images as input. The obtained results are compared with some recent algorithms for SR proposed by Yang *et al*. (2013) and bi-cubic interpolation technique. The open source implementation of this algorithm available online was used for comparison.

The scaling factor chosen was r=2 and the image patch size used was a=5 in the test experiment. Standard deviation value of 0.4 was used in low pass Gaussian filtering to obtain the low frequency component of the input image. The dictionary was formed using a single image as input. For training and updating the dictionaries D_h and D_l, k=512 atoms was used.

The proposed SR algorithm was tested using various test images and the obtained results are shown in Fig.3. It also compares the obtained result with other SR algorithms like bi-cubic interpolation and Yang *et al*. (2013). From Fig.3, it can be seen that the proposed SR algorithm produces more natural looking images compared to the other methods. Peak signal to noise ratio (PSNR), root mean square error (RMSE) and structural similarity index measurement (SSIM) are computed for the obtained results to measure the performance of the proposed SR algorithm,. The above stated measures are used to qualitatively estimate the performance of the proposed SR algorithm compared with other algorithms.

The PSNR values obtained for all the technique are shown in Table.1. From the PSNR values, it is found that bi-cubic technique performs worst as it uses smooth image priors. The comparison between the RMSE values of all images is given in Table.2. The proposed algorithm has the least mean square error value compared to the other SR algorithms. The Structural similarity index measurement (SSIM) is used to check the quality of obtained images. Structural similarity is a measure of similarity between images. The SSIM index for the obtained images are computed and tabulated in Table.3. The propose SR technique performs well compared to the other techniques as it uses in-place example patches along with self-learned dictionary based on sparsity.

Table 1: PSNR (dB) measurement for scaled images (2X) using various SR algorithms

Images	bi-cubic	Yang[16]	Proposed
Lena	32.134	32.780	33.011
Peppers	27.957	30.643	30.824
Baby	31.753	33.218	33.593
Cameraman	25.554	27.1947	27.259

Table 2: RMSEmeasurement for scaled images (2X) using various SR algorithms

Images	bi-cubic	Yang[16]	Proposed
Lena	6.307	5.855	5.701
Peppers	10.201	7.487	7.333
Baby	6.589	5.566	5.331
Cameraman	13.453	11.138	11.055

Table 3: SSIM measurement for scaled images (2X) using various SR algorithms

Images	bi-cubic	Yang[16]	Proposed
Lena	0.992	0.997	0.998
Peppers	0.892	0.991	0.994
Baby	0.994	0.995	0.998
Cameraman	0.841	0.817	0.887

Conclusion:

In this paper, a SR algorithm based on local regression model is developed. It uses the advantages of both first order and second order regression model. The relationship between the LR and HR image patch is derived from the local regression model. The regression model makes it easy to determine the LR-HR patch mapping function. From various experiments, we show that our proposed algorithm produces good results and can work efficiently on various images with diverse textures. Image reconstruction using the first order regression function can effectively suppress noise and artifacts, but does not eliminate blur. Whereas the second order regression model can be used to suppress blur. Thus our proposed algorithm combines both first order and second order model for image SR. Thereby it includes the advantages of using both first order and higher order regression model. The proposed algorithm can efficiently reconstruct images degraded with noisy artifacts and blur.

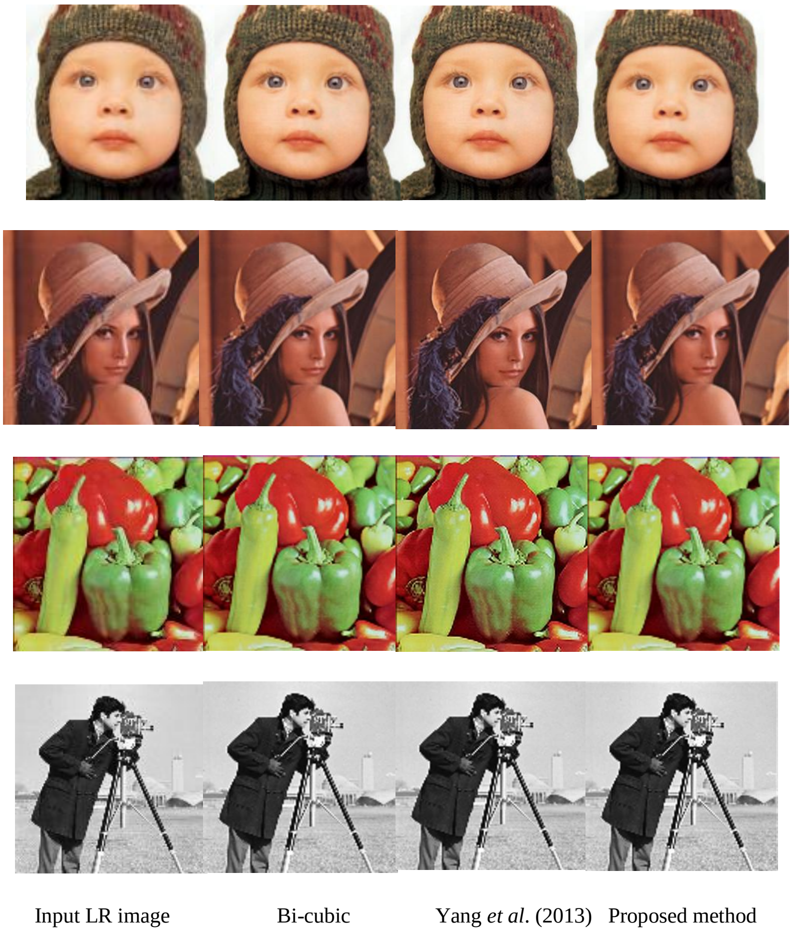

Fig. 3: Results of SR (2X) on “child”, “lena”, “peppers” and “cameraman”.

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