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Single Image Super Resolution Reconstruction using an Unsupervised Learning Framework

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Abstract: Recently image super resolution (SR) has become an important research area to generate high resolution (HR) image from given low resolution (LR) image. The main aim of super resolution is to improve visual quality of available low resolution image. So the existing low resolution imaging systems can be used. The need for extracting high quality image arises in the fields of medical imaging, remote sensing, biometrics identification and pattern recognition. In this paper we have focussed on single image super resolution where only one low resolution image of the scene is available. We have approached SR using learning based techniques. Support vector regression (SVR) along with image sparse representation has been used in our framework to model the relationship between images and their allied SR versions. In comparison to other example based SR methods, the proposed method does not require the collection of training data in advance. The SVR models have been extended to the use of multiple kernel learning for adaptive kernel selection. Simulation experiments have been performed on a variety of images, and results indicate an improvement in visual fidelity and numerical measures.

Keywords: Kernel learning, low resolution, high resolution, sparse representation, support vector regression, super resolution.

I. INTRODUCTION

High resolution (HR) images are preferred and required for most digital imaging applications for processing of images and their analysis. High image resolution is required for refining the pictorial information for human interpretation and helping representation for automatic machine perception. HR images are desired in pattern recognition, medical imaging, remote sensing, and biometrics identification. Image resolution can be increased by reducing the pixel size or by increasing the chip size of the sensor which are constrained by the physical limitations of the imaging systems [1]. Therefore a promising approach is to use signal processing algorithms to realize resolution enhancement. The process of obtaining a HR image from a single low resolution (LR) image or multiple LR images is called super-resolution (SR). Accordingly, SR reconstruction can be broadly classified into two classes: (i) Single-image SR methods, and (ii) Multi-image SR methods. In multi-image SR [2], [3], [4], [5], multiple LR images with different sub-pixel shifts of the same scene are taken as input. As there exists multiple HR images that result in the same LR image a set of constraints are imposed on the unknown HR image along with a regularization and prior term to transform the ill-posed SR problem to a well-posed one. It is applicable for video SR where multiple frames are available.

Other class of SR methods produces HR image from a single LR image. The aim of single-image super resolution reconstruction (SISR) is to obtain a HR image X from an observed LR image Y: Y=NQX + V, where N, Q and V represent the down sampling operator, blurring operator and noise respectively [6]. The SISR approaches can be mainly categorised into three classes: regularization methods [7], interpolation methods [8], and learning-based SISR methods [9], [10]. The performance of regularization methods degrades when magnification factor becomes large whereas interpolation based methods are limited in modelling the visual complexity of real images. In learning-based method, a HR image is predicted by modelling the relationship between a set of LR and HR training image patches. The difficulty in learning-based SR methods lies in the proper selection of training data and appropriate learning models for SR from an unseen target image. Regression models like linear, Bayesian, polynomial, etc. can be used to provide a relationship between known LR image and unknown HR image by using a function model with estimated parameters. But the above mentioned static function models are limited in their domain space, and hence the image content may not be well represented with these restrictions. It will be more effective to use functions in high-dimensional feature space to learn this relationship. This can be realized by using support vector regression (SVR) which has the capability in predicting the functional outputs without any prior knowledge (e.g. data distribution, etc.) of the training data. SVR based SR methods require the training image pairs in advance and it might limit their practical use. To overcome this limitation we propose a self-learning framework for SR.

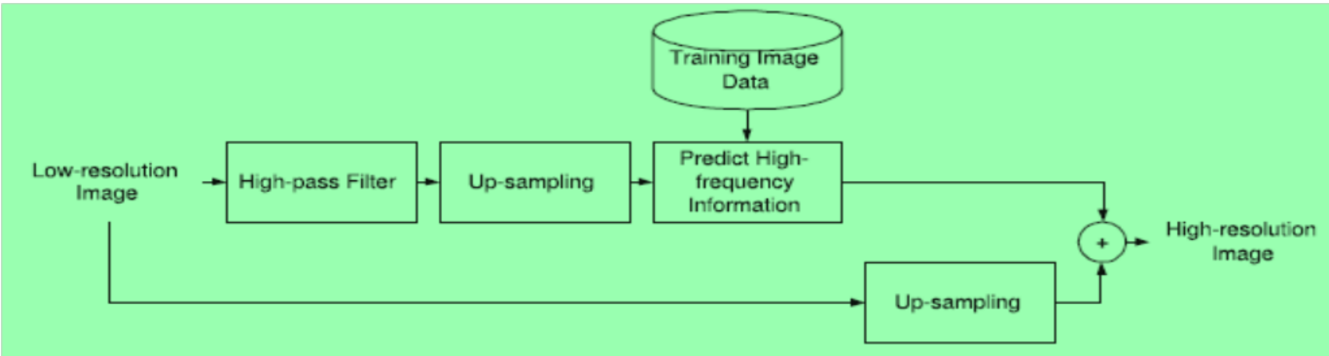

Fig. 1. A conceptual framework of learning based SR image approach

II. UNSUPERVISED LEARNING FRAMEWORK FOR SINGLE IMAGE SR

In this section we will describe our proposed unsupervised learning framework for single image SR. In this approach, there is no need to manually and carefully select the training image data which is not practical for real world SR applications. There is no assumption of image patch self-similarity in this framework. Fig. 2 gives the overview of the SR approach. Image I_0 is the input LR image, and I_{SR} is the final SR output. Instead of searching for similar image patches from the different down-scaled versions $\{I_{-1}, I_{-2} \ldots\}$, a relationship is modelled between images from each scale. Once these models are observed for each scale, the best ones are selected to refine each patch S' (up sampled version of I_0) into output I_{SR}. Image sparse representation is used as an effective feature for learning.

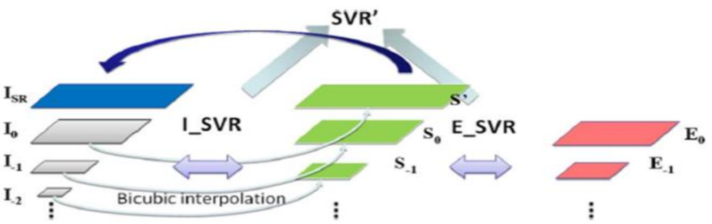

Fig. 2. Self-Learning framework for single image SR

A. Learning of Image Sparse Representation

Bicubic interpolation is used to synthesize input LR image into its HR version. After all 3 x 3 pixel patches are extracted from this synthesized image, proper features need to be selected to describe each patch to learn the SR models. Sparse coding is used to represent the image features. The advantage of using sparse image representation is that training and computation time will decrease as most image feature attributes will be zero. To determine the sparse representation for the patches, an over complete dictionary is learned from the extracted patches and the resulting sparse coefficients are the features of interest. To learn the dictionary, the tool developed by [11] is used to learn the dictionary D and the associated sparse coefficients α for each patch. This is formulated as the following optimization problem:

$$\min \frac{1}{2} ||D\alpha - x||_2^2 + \lambda ||\alpha||_1 \qquad (1)$$

Where x is the image patch of interest, D is the over-complete dictionary, and α is the corresponding sparse coefficient. The Lagrange multiplier λ balances the sparsity of α and l_2 norm reconstruction error. The image patches are divided into high and low spatial frequency ones and their dictionaries are learned accordingly.

B. Support Vector Regression

SVR is an extension of support vector machine (SVM) and has the ability to fit the data in a high-dimension feature space without assumption of data distribution. SVR is capable of predicting the unknown outputs effectively. In training, SVR [12] solves the following problem:

$$\begin{gathered}\min_{w,b,\varepsilon,\varepsilon^*} \frac{1}{2} w^T w + C \textstyle\sum_{i=1}^{n}(\varepsilon_i + \varepsilon_i^*) \\ \text{s.t}\ \ y_i - (w^T\Phi(\alpha_i)+b) \leq \epsilon+\varepsilon_i, \\ (w^T\Phi(\alpha_i)+b) - y_i \leq \epsilon+\varepsilon_i^* \\ \varepsilon_i, \varepsilon_i^* \geq 0, i = 1, \ldots\ldots, n. \end{gathered} \qquad (2)$$

In (2), y is the pixel value at the same location as the centre of the patch of interest in the HR image, b is the off-set parameter of the regression model, $\Phi(\alpha_i)$ is the sparse image representation, n is the number of training patches, w is the norm vector of the nonlinear mapping function, C is the trade-off between the generalization and the training error bounds ε_i. and ε_i^*, subject to margin ∈. Once the SVR training is complete, the observed SVR is applied to predict the final SR output. As shown in Fig. 3, bicubic interpolation is used to synthesize the HR version from the test input image. Then the sparse representation is derived for each patch and centre pixel value is updated using the learned SVR model.

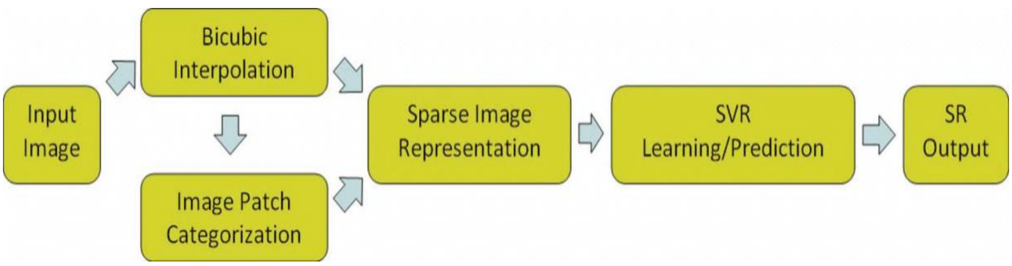

Fig. 3. Flowchart for synthesizing an SR image. This framework does not require the collection of training low and high resolution data in advance

C. Unsupervised Learning of SVR for Image SR

The resolution of the input LR image I_0 is downgraded into low resolution versions $\{I_{-1}, I_{-2} \ldots\}$. Then these images are interpolated to synthesize the associated HR images using bicubic interpolation. So two image pyramids $\{I_i\}$ and $\{S_i\}$ are obtained. Each image I_i can be regarded as the ground truth image of its interpolated version S_i. Then sparse image representation is extracted for each patch in S_i. Later SVR is applied to model the relationship between S_i and I_i. Then we obtain the set I_SVR = {I_SVR$_0$, I_SVR$_{-1}$…} as the collection of SVR models observed from different image scales. SVR is subject to training errors ε_i

and $\mathcal{E}_i^*$ with precision $\in$. So the predicted result of S_i using I_SVR may not be same as I_i, and the error image E_i is obtained. The pixels of the error image are calculated as:

$$e_{ij} = ||I_{ij} - \text{I\_SVR}_i\ (\alpha_{ij})\ ||,\ i=0.-1,\ldots \qquad (3)$$

Where I_{ij} is the j-th pixel value in image I_i, α_{ij} is the sparse representation of the j-th patch in S_i. Once E_i is obtained another SVR regression model E_SVR_i is used to model the relationship between S_i and E_i. To summarize, first the image pyramids I_i and S_i are constructed from a given LR input image. SVR models E_SVR and I_SVR are then observed from different image scales. Then the errors are predicted using E_SVR for each patch in S' to obtain the final SR output I_{SR}. Once the smallest E_SVR_i is determined, then the corresponding I_SVR_i is used for further refining.

III. EXPERIMENTAL RESULTS AND ANALYSIS

In this section, we present the efficiency of the proposed method to recover the super-resolved image from a number of test images at different magnification factors. The simulation experiments were carried out using Matlab on Windows 7 OS with 2 GB RAM and 2.30 GHz Intel processor. SVR models used in this framework are trained using LIBSVM [13]. We have used mex code for some of the sub routines. When processing color images, the image is transformed from RGB to YIQ. Then the algorithm is applied only on the intensity channel Y. Then the I and Q channels are interpolated using bicubic interpolation. The dictionary is constructed using [11], and the dictionary size is set to 100. The performance measure used to evaluate the results is peak signal-to-noise ratio (PSNR). Various edge detection techniques have been used on each of the test image for testing the effectiveness of each technique.

$$\text{PSNR} = 10.\log_{10}\left(\frac{\text{MAX}^2{}_I}{\text{MSE}}\right) \qquad (4)$$

$$= 20.\log_{10}\left(\frac{\text{MAX}^2{}_I}{\text{MSE}}\right) \qquad (5)$$

$$= 20.\log_{10}(\text{MAX}_I) - 10.\log_{10}(\text{MSE}) \qquad (6)$$

Where MAX_I is the maximum possible pixel value of the image. The higher the PSNR value, the better will be the reconstruction of the image.

$$\text{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\ \sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \qquad (7)$$

Where i and j are the rows and columns of the image.

Table I lists the PSNR for three different test images with magnification factor of 2 and 3. We have used three different edge detection techniques namely, canny, sobel and prewitt. It can be inferred that canny detection technique gives better PSNR values in comparison with sobel and prewitt. Table II shows the comparison of PSNR values obtained by the proposed framework over other state of art SR methods. From this table, it can be observed that SR by sparse image representation outperforms the bicubic interpolation method. The scheme proposed provides PSNR improvements and offers better visual quality.

Fig. 3 and Fig. 4 shows the SR results obtained for lena image and butterfly image with a magnification factor of 2 and 3 respectively. Comparing the SR images produced by various methods, we can infer that our scheme produced satisfactory result with the highest PSNR value.

TABLE I

PSNR (dB) OF DIFFERENT TEST IMAGES WITH MAGNIFICATION FACTOR OF 2 AND 3

Test Image	**Scale Factor**	**Edge detection**		
		Canny	***Sobel***	***Prewitt***
Butterfly	2	34.97	34.62	34.64
Butterfly	3	39.07	38.61	38.80
Eyetest	2	26.74	26.38	26.30
Eyetest	3	29.74	29.02	29.04

Lena	2	36.29	36.20	36.27
Lena	3	41.75	41.40	41.74

TABLE II
COMPARISON OF PSNR (dB) VALUES OBTAINED BY DIFFERENT SR TECHNIQUES ON VARIOUS TEST IMAGES

Test Image	**Scale Factor**	**Bicubic Interpolation**	**Yang et al. [14]**	**Proposed scheme**
Butterfly	2	25.97	32.33	34.97
Butterfly	3	25.52	32.86	39.07
Eyetest	2	22.26	26.22	26.74
Eyetest	3	21.20	26.25	29.74
Lena	2	28.73	30.41	36.29
Lena	3	28.39	31.24	41.55

(a) (b) (c)

Fig. 4. Comparison of super resolution results for Lena image (with magnification factor 2) using proposed method over other state-of-arts methods: (a) Bicubic interpolation (PSNR: 31.49) (b) Yang et al. [14] (PSNR: 35.03) (c) Proposed scheme (PSNR: 39.20)

Fig. 5. Comparison of super resolution results for Butterfly image (with magnification factor 3) using proposed method over other state-of-arts methods: (a) Bicubic interpolation (PSNR: 28.03) (b) Yang et al. [14] (PSNR: 32.80) (c) Proposed scheme (PSNR: 38.08)

IV. CONCLUSION

In this paper, we have provided a technique of obtaining a super resolved image from a single low resolution observation. The proposed method is different from the conventional super resolution techniques where one tries to recover the super resolved image from several low resolution observations of the same scene. An unsupervised-learning framework for single image SR has been proposed. We have used support vector regression and image sparse representation in our framework. This approach is unique since it does not require the collection of training low and high-resolution image data beforehand. The proposed method produces good SR results on a variety of images and there is a significant improvement in PSNR when compared to the other SR approaches. Future work can be directed towards the resolution enhancement of digital video and stereo imaging.

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