Multiple Kernel Regression Based Image Resolution for JPEG Images

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ABSTRACT

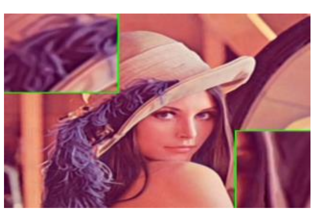
Now A days Image Super-Resolution is active research topic due its widespread use in many practical application. Recently Learning –Based Approach for Super–resolution (SR) has been used which generate favorable result. In this paper image super –resolution based on the multiple kernel regression is presented. This approach's core is to learn the map between the space of high resolution image patches and the space of blurred high – resolution image patches. Which is the interpolation result generated from corresponding low-resolution image. Here using multiple kernel instead of single kernel for regression. Because choosing appropriate single kernel form image is difficult and time consuming rather than dividing image into multiple sub-band and each sub-band has own kernel. And Finally use Support Vector Regression (SVR) to fit the data in high dimensional feature space. The experimental result show that it achieve three time better quality of image than other.

Keywords: *Super resolution, Linear kernel regression, Support Vector Regression, Low Resolution Image, Interpolation, Sparse Representation.*

1.Introduction

Super resolution (SR) has been active research topic in the area of image processing and computer vision. Image super resolution aims to get a high- resolution (HR) image from single low–resolution (LR) image or multiple low-resolution (LR) images. The HR image contains more details than the LR one, it is beneficial in many applications, such as medical imaging, video surveillance, and remote sensing. Many image SR methods have been proposed in the past few decades [7].

Normally More number of pixels gives more detailed visibility of information contained in the image but hardware has limitation that restrict the increasing number of sensor elements per unit area in camera. Therefore imaging system will generate Low Resolution image which cause not getting proper information from image. To overcome this problem use resolution enhancement which is usable process for many image processing application such as Geoscience Studies, Astronomy, Geographical information system.



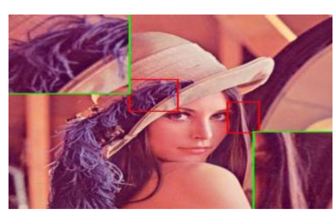


Fig 1: Before[3] Fig 2: After[3]

It increasing the spatial resolution of on image from image itself. There are many application of Super-Resolution in area of image processing such as Target detection, Recognition, Tracking has many application in consumer product like cell phone, webcam, HDTV, CCTV.

Fig 1 Show the image before applying any enhancement on image. Clarity of an image is not good for square portion so not getting the exact information from that pixel. Fig 2 show the image after applying resolution enhancement and obtain patch by patch clarity of an image. So getting exact information form that selected portion or pixel.

2. BACKGROUND THEORY

In general, the approaches for SR can be categorized into three classes :

1) Interpolation based methods,
2) Reconstruction based methods,
3) Learning based methods

Interpolation based methods [3] are based on sampling theory. This method involves prediction of unknown pixel by filtering process. They are simple and fast, but the quality of results is very limited, because they cannot recover the high frequency details and they tend to produce ringing and jagged artifacts[6]. It perform well in smooth area but not well in edge area.

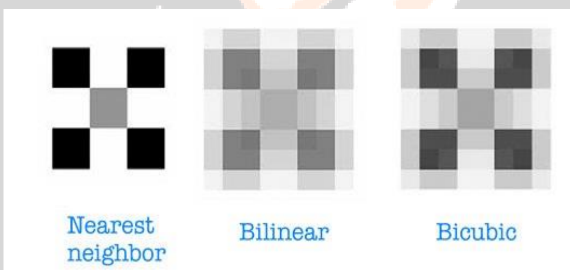
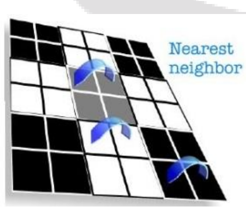


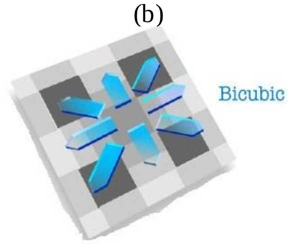
Fig 3: Type of Interpolation[11]

There are type of interpolation: 1]. Nearest Neighbor interpolation which require least processing time because it consider only one pixel which is closest to central pixel. But in result some edges are lost.



(a)

(b)



(c)

Fig 4: Classification of interpolation (a) Consider only one neighboring pixel (b) consider 2*2 neighboring pixel (c) consider 4*4 neighboring pixel [11]

2].Bilinear Interpolation which consider 2*2 neighbor of unknown pixel and take 4 pixel to arrive at interpolated point and obtain smoother image than above but it give blurred image. 3].Bi-cubic Interpolation which goes one step beyond bilinear by considering the closest 4*4 neighbor of known pixel that given higher weighting sharper image and smoother curve.

Reconstruction based method [2], [3], [4] estimate an SR image from LR by applying some prior knowledge to the up-sampled image. These methods require that the smoothed and down -sampled version of the HR image should be close to the original LR images. This achieved by alignment of multiple LR image patches of the same sub pixel level accuracy. According to[4],the magnification factor of reconstruction-based SR approaches is limited to be less than 2 for practical applications. Moreover, when an image does not provide sufficient patch self-similarity, single-image reconstruction based methods are not able to produce satisfying SR results. The performance of these reconstruction-based SR algorithms degrades rapidly with the increase of the magnification factor and the decrease of the size of the input image.

To overcome the limitations of reconstruction-based algorithms, machine learning-based techniques have been proposed [1].This method use a database consisting of pairs of LR and HR images as the training set to estimate high frequency details via learning the relationship between them. These methods can effectively recover missing details. This type of algorithm usually consists of two steps[1]: (1) capturing the coherence from a training data set that includes both LR and HR image patches; and (2) predicting the details of the HR image through such prediction methods as Markov random field or locally linear embedding. In learning based SR methods, regression based SR methods prove to be an effective tool for the SR problem[3]. The goal of regression is to find the underlying signal in a given data. The assumption made here is that the given signal is corrupted with some noise. The work in [2][3] implemented Support Vector Regression (SVR) in the frequency domain and used a kernel learning method to solve the SR problem.

Its drawback was that the solution of SVR was dense which is computational demanding in training and testing. Each pixel value in an HR image is estimated from the corresponding blur patch extracted from the blur HR image.

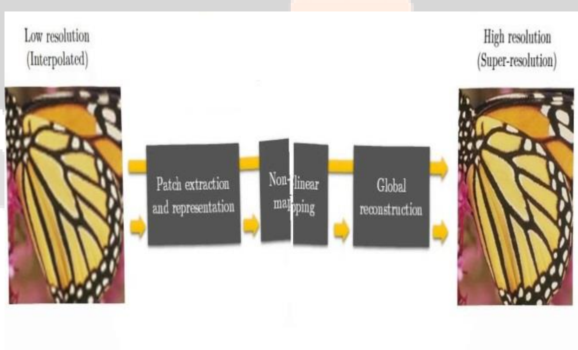


Fig 5: Basic idea of Learning based super resolution[12]

3. Literature Survey

Now a days there are many way and method are available to obtained super-resolution from low resolution image.

Iterative Enhance d Super Resolution System(IESR) [8] is one of them, which is based on two- pass edge dominated interpolation by adaptive enhancement and dithering mechanism. In this method Iterative Back Projection Concept is used to projects the error between simulated and input LR image to estimate HR error by minimizing reconstruction error. The adaptive image enhancement algorithm can improve the distorted high-frequency parts while the adaptive dithering method can recover the loss of high-frequency components. But Computation time are large for this method and quality of image is limited.

Another is hybrid method[7] consisting of steering kernel regression (SKR) and example based super-resolution (EBSR) techniques to obtain SR image. In this model the output of SKR is given as the input to the EBSR module. Image super-resolution performed by SKR gives a reasonable result, in terms of perceptual quality, the regression techniques have generating artifacts. EBSR on the other hand augments the image with high frequency information to the image, thereby sharpening the edges. Here Computation time is large and it is little complex.

Learning multiple adaptive interpolation kernels[1] also used to enhance image. It is overcome the disadvantage of dual learning. It is Based on the assumptions that each high-resolution image patch can be sparsely represented by several simple image structures and that each structure can be assigned a suitable interpolation kernel. Here focus on the following two topics: (1) clustering the training database of LR and HR image patches into several classes; and (2) learning the interpolation kernel of each class. This approach preserve sharp edge and it is faster.

self-example-based method[5] is used for enhancing image. Patch redundancy and patch similarity in image pyramids is used to improve the image resolution. Also steering kernel regression for patch similarity are used in the image reconstruction. For avoiding over-smoothing the structure of image, an automatic metric is presented to preserve the structure better. They use steering kernel regression (SKR) for local structural constraints. They add local SKR regularization for image super resolution.

Multikernel Regression Method[3] is also used to reconstruct super resolution image from low resolution image. It is very efficient method than other method because it avoid selecting kernel which is critical problem. In this method learning the relationship between LR feature space and HR feature space.

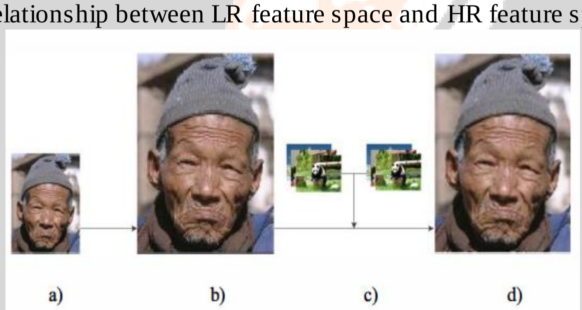


Fig 6: The processing pipeline of our approach. (a) The input LR image.(b) Upsampled blurred image generated by nearest neighbor interpolation.(c) Using training set to obtain kernel functions. (d) The HR image recovered.[3]

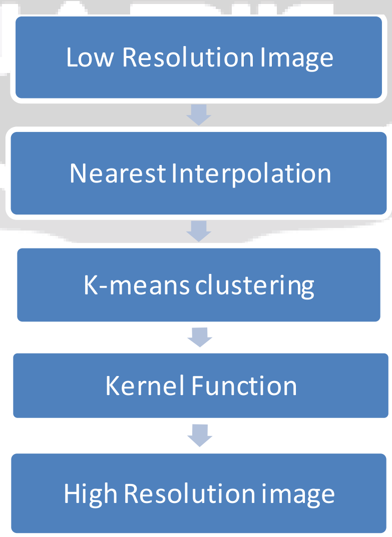


Fig 7: Flowchart of existing method

They focus on the problem of recovering the SR image of a single input LR image. Processing Pipeline[3] of their approach is 1) Given an LR image , they firstly interpolate it into the desired scale , and 2) then use the learned fitting function to produce a high resolution image which recovers the missing high frequency. 3) Given an LR image, they firstly interpolate it into the desired scale , and then use the learned fitting function to produce a high resolution image which recovers the missing high frequency details.

Take an input Low Resolution image. Given an LR image , they firstly interpolate it into the desired scale. Interpolate this LR image by using Nearest neighbor interpolation and obtain blur image. Get key patches by using k-means. Before using training set, there is need to select key patches by using k-means to construct linear kernel matrix. There are also available Orthogonal matching pursuit for construct linear kernel matrix. If training data N is 20000 but, By using OMP kernel matrix is 20000*20000 and By using k-means take nearest neighbors of sample is 300 so kernel matrix is 20000*300. Apply kernel function on each key patches. Given a training set {(Xl, xI) , ... , (XL, xL)} where Xl denotes the blur HR patch, and xI is the corresponding HR patch, we solve the regression functions by minimize the following cost function:

$$f^i(x) = \sum_{j=1,\ldots,L} a_j^i k(\widetilde{x}_j, x)$$

Then finally Combine all image patches and Get high resolution image.

4. PROPOSED SYSTEM

In this paper, present Multiple Kernel Regression with bi-cubic interpolation and support vector regression by using sparse representation. By this method obtain three time better quality super resolution image. By this method obtain three time better quality super resolution image.

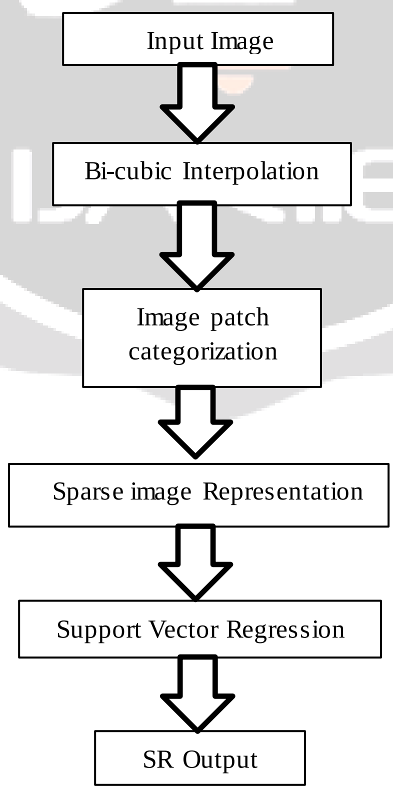


Fig 8: Flowchart of multiple kernel regression based super resolution

1st of all take an input low resolution image. Then apply Bi-cubic interpolation on an input image. Here choose Bi cubic interpolation rather than Nearest interpolation or Linear interpolation because bi-cubic is extension of cubic interpolation for interpolating data. This interpolated surface is smoother than other. It considering the closest 4*4 neighbor of known pixel that given higher weighting sharper image and smoother curve. Now, Apply Image patch Categorization on interpolated image. This regression is based on patch by patch in training set. The super-resolve an LR input patch, they searched for similar patches from the image pyramid. With the help of this patch categorization, obtain similar patches from image so can easily find the value of each pixel.

Next step is to apply sparse image representation on patch categorized image or interpolated image. Sparse representation give updated central pixel value for each data set. By this obtain constant patches in data set for further processes. To obtain sprase representation map estimation is needed. In Image Processing a Kernel is Small matrix or mask useful for Blurring, Sharpening, Embossing, Edge detection and more. In Image Processing a kernel is simply a two dimensional matrix of numbers. This is accomplished by means of convolution between kernel and image. Depending on the element values, a kernel can cause a wide range of effects.

Multiple Kernel

Here using multiple kernel for regression to estimate random variables. Objective is find new linear relationship between a pair of random variable. Kernel regression based super resolution is promising but the kernel selection is critical problem. Because choose single appropriate kernel form image is too difficult and time consuming. In order to avoid selecting the kernel via large amount of cross verification, the multiple kernel regression applied to map estimation. By partitioned image into multiple sub-band in that case choosing a kernel from each sub-band is easy and not time consuming. Multiple kernel instead of single kernel can enhance interoperability of decision function and improve classifier performance.

Support Vector Regression

Then Finally use Support Vector Regression on resulted image. Support vector regression (SVR) is an extension of support vector machine, which is able to fit the data in a high-dimensional feature space without assumptions of data distribution. It has the generalization ability that is very powerful in predicting unknown outputs, and the use of SVR has been shown to produce effective SR outputs.

Goal of SVM is to design a hyperplan that classifies all training vector in classes. There are another hyperplanes but choice of hyperplane is which has maximum margin from classes. SVM separating data by following steps : First of all SVM find closet two point referred as **Support Vector** from two classes that define best separating line. Then draw line that connecting two point, support vector. SVM decide that the best separating line is the line that **Bisects** and is **Perpendicular** to the connecting line[12]. SVM can be applied not only to classification problem but also case of regression. It contain all main feature that characterize maximum margin algorithm: Non-linear function lean by linear learning machine mapping into high dimensional kernel include feature space. The goal of regression is to find the underlying signal from the given data by combination of local data and appropriate weight.

Basic properties of the SV algorithm for regression are described. Figure contains a graphical overview over the different steps in the regression stage. The input pattern (for which a prediction is to be made) is mapped into feature space by a map. Then dot products are computed with the images of the training patterns under the map. This corresponds to evaluating kernel functions $k(xi , x)$. Finally the dot products are added up using the weights $vi = \alpha i - \alpha i$. This, plus the constant term b yields the final prediction output[12].

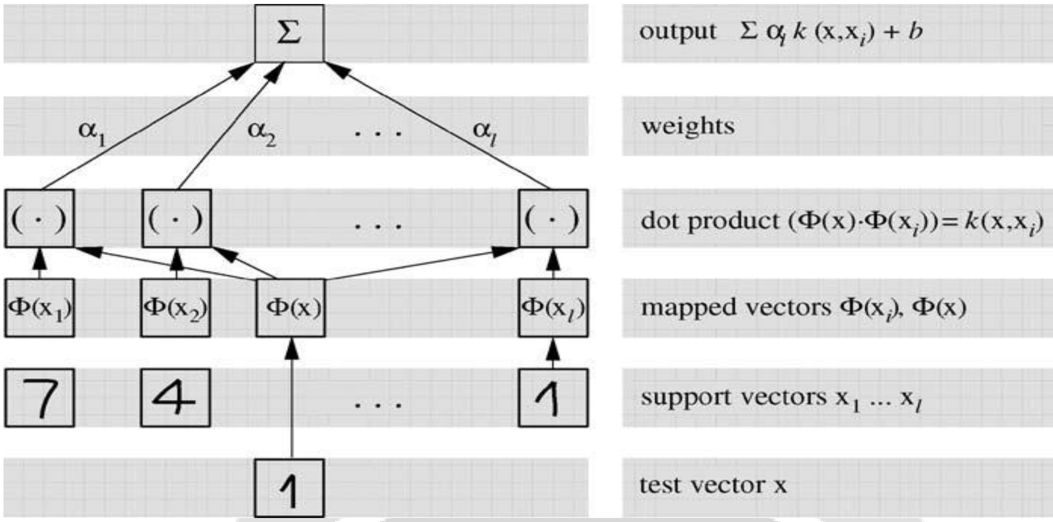


Fig 9: Flow chart of Support vector regression[12]

5. RESULT ANALYSIS

We test our proposed method on the popular images and evaluate our proposed method. The parameters used in the experiments are shown in table 1. There are two parameters to be determined: Peak signal to noise ratio (PSNR) and Feature similarity index for image quality. PSNR is the ratio between maximum power of signal and power of corrupting noise. It is the measurement between original input image and resulted output image by representing measure of peak error. Feature similarity index is measure the quality of image by feature similarity. Human visual system understands an image mainly according to its low level features. Which is based on two feature: Phase congruency (PC) and Gradient magnitude (GM).

We compare our approach with three other approaches: the bi-cubic interpolation (Bi-cubic), the linear kernel regression and the support vector regression (SVR). Figure 10,11 shows some comparison results visually. For the first result just apply bi-cubic interpolation which obtain better result than other in case of smoother curve but not maintain the quality of image. For the second result apply linear kernel regression which is accurate but it lost the high frequency of component .And the third result is obtain by applying Support vector regression with multiple kernel regression which prevent the high frequency component and obtain higher quality of image. In comparison, our approach achieves the best visual effect and the results are closest to the original image.

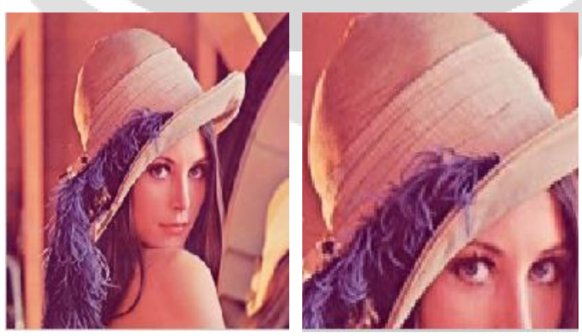


Fig 10: Input LR image and zooming effect on LR image

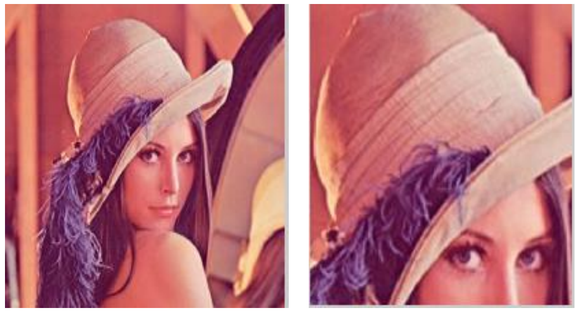


Fig 11: Output SR image and zooming effect on SR image

For implementation of proposed Flow work has been experimented through matrix laboratory software (MATLAB), which is running on laptop with a 2 GHz Core2duo with 2GB RAM and Windows 8 Operating System. These figure how that our results are superior to the other three approaches according to the visual effect. The results of bi-cubic and kernel regression contain some obvious block effects, and support vector regression produces poor visual quality such as blurring and jagging artifacts. In comparison, our approach achieves the best visual effect and the results are closest to the original image. We also evaluate our approach in terms of PSNR and FSIM. As shown in graph, our approach achieves the highest PSNR and FSIM values. The size of the input image is 15kb and the size of the output image is 51kb.

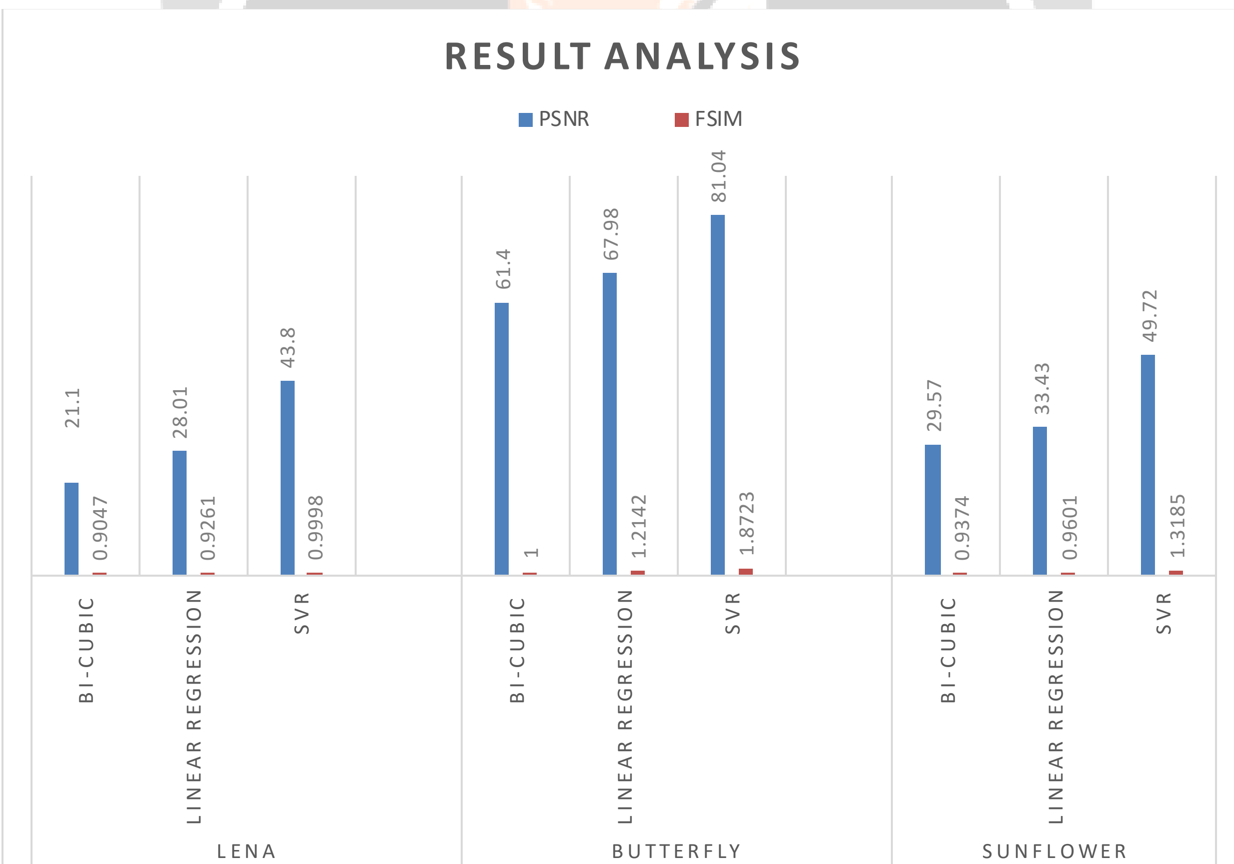


Fig 12: Result analysis of 3 different images

6. CONCLUSION

Resolution has been frequently referred as an important aspect of an image. Images are being processed in order to obtain more enhanced resolution. There are various technique for enhancing high resolution image from low resolution image. Multikernel regression learn map between the high resolution image patches and blurred high resolution image patches which are the interpolation result generated from the corresponding low resolution image by Bi-cubic interpolation and then using Support Vector Regression and gain three time better quality of super resolution image.

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