Multiple Kernel Regression Based Image Resolution for JPEG Images

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Abstract:* Recently Learning –Based Approach for Super–resolution (SR) has been used witch 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.That are the interpolation result generated from corresponding low-resolution image. The super-resolution image reconstruction can be transformed to solve linear equations whose size depends on the number of the training data. When the amount of the training data is large, it is time-consuming to solve the regression problem. To solve this problem select part of pairwise patches from training database instead of all the training data. In this method use Support Vector Regression(SVR) to generalize unseen data and unknown function. 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***

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

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

1) Interpolation based methods,
2) Reconstructionbased 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.

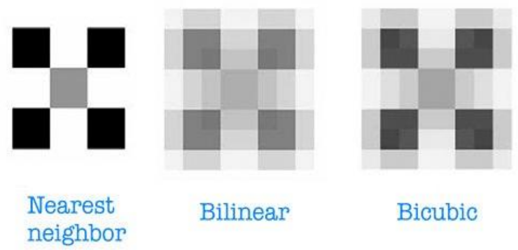

Fig 2: Type of Interpolation [11]

There is 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.

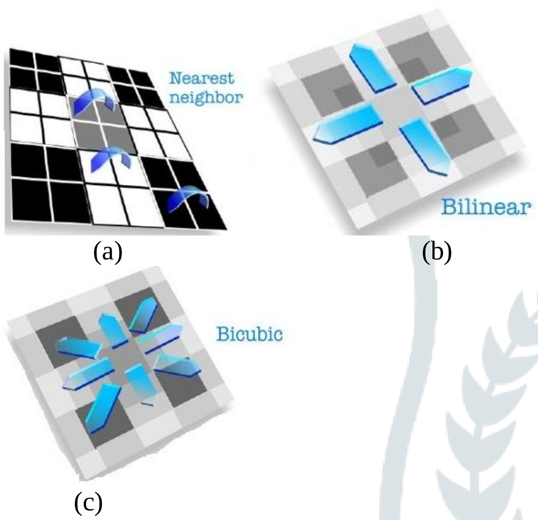

Fig 3: Classification of interpolation (a) Consider only one neighboring pixel (b) consider 2*2 neighboring pixel (c) consider 4*4 neighboring pixel [11]

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].Bicbic 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. It require image patches from one or several images when synthesizing the SR output.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 . Although some regularization based approaches, were proposed to alleviate the above problems, 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.

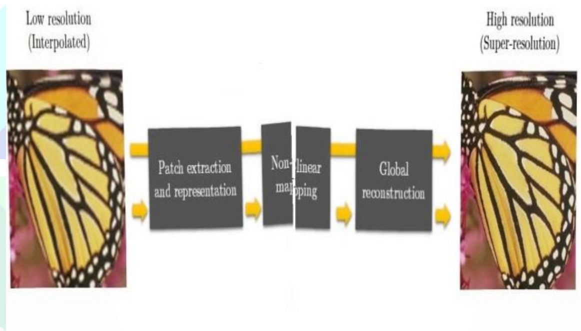

Fig 4: Basic idea of Learning based super resolution [12]

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.

3. EXSITING SYSTEM

Now 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 theadaptive dithering method can recover the loss ofhigh-frequency components. But Computation time is 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. HereComputation 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.

Multi kernel 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.

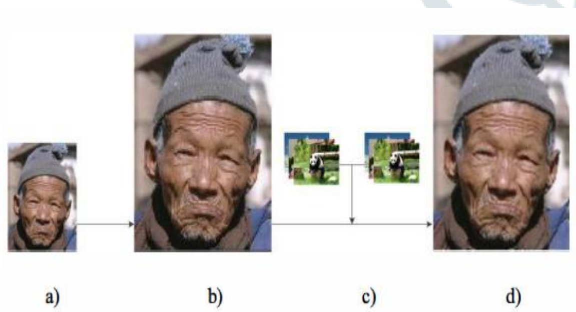

Fig 5:The processing pipeline of our approach. (a) The input LR image.(b)Upsampled blurred image generated by nearest neighbor interpolation.(c) Using training set to obtain kernel functions. (d) The HR imagerecovered.[3]

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 intothe 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.

Theneed to find appropriate kernel for that Given a training set
$\{(\widetilde{x}_1, x_1), \ldots, (\widetilde{x}_L, x_L)\} \subset R^N \times R^N,$
Wherex1 denotes the blur HR patch, and x_I is the correspondingHR patch, we solve the regression functions by minimize the
Following cost function

$$\varepsilon(f) = \sum_{i,\ldots,N} (\sum_{j=1,\ldots,L} (f^i(\widetilde{x}_j) - x_j^i)^2)$$

They predict the HR image for a single input LR image by a coarse-to-fine process which includes two steps. And this process can be defined as:

$$\widetilde{H} = L \uparrow^m$$
$$H = f * \widetilde{H}$$

Where L denotes the inLR image and H denotes the HR image respectively, and H denotes the blur HR image, and m denotes the interpolating operation with amagnification factorm, and f denotes a deblurring operation using kernel functionvectors. Using this method achieve highly computational efficiency and good performance, fast computation speed.

Experimental results on three real-world Super Resolution images demonstrate that the proposed framework can lead to a significant advancement in these two applications compared with other competitors.

Sr No	Paper Title	Method Name	Advantage	Disadvantage
1	Learning adaptive interpolation kernels for fast single-image super resolution	Multiple Adaptive Kernel	Preserve Sharp edge, and faster than other	Not useful for real-time images
2.	Image Super-resolutionBasedOn Multikernel Regression	Multikernel Regression	Achieve highly computational efficiency and good performance, fast computation speed	Experimental result show Fewer jaggy effect or ringing artifact

3	Multi-Scale Single Image Self-example-based Super Resolution Based on Adaptive Kernel Regression	Adaptive Kernel Regression	Avoid over smoothing and get high resolution image	Sometime generate jaggy artifact on some edge
4	Hybrid Method for Image Super-Resolution Using Steering Kernel Regression and Example-based Approaches	Steering Kernel regression Example based SR	Preserve more detail , avoid denoising and enhance high frequency content	Computation time is large and little complex
5	An iterative enhanced super-resolution system with edge dominated interpolation and adaptive enhancements	Iterative Enhanced Superresolution (IESR) system	Overcome the artifact of interpolation and Recover loss high frequency component	Computation time are large and quality of image is limited

Table 1. Literature review of different methods

Multiple Kernel Regression with bi-cubic interpolation and support vector regression using sparse representation. By this method obtain three time better quality super resolution image. Multiple Kernel Regression with bi-cubic interpolation and support vector regression using sparse representation. By this method obtain three time better quality super resolution image. This regression is based on patch by patch in training set. If it is not needed to categorization then direct sparse representation is apply. The super-resolve an LR input patch, they searched for similar patches from the image pyramid and use the associated sparse representation to predict its final SR version. Sparse representation give updated central pixel value for each data set. By this obtain constant patches in data set for further processes. 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.

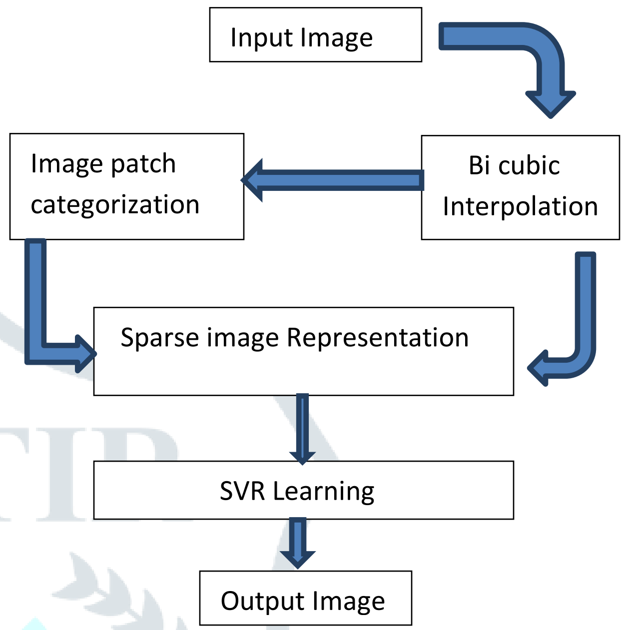

Fig 6: Flowchart of multiple kernel regression based super resolution

4. 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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