Single-Image Super-Resolution Using Active-Sampling Gaussian Techniques

[1]Dr.I.Santhi Prabha, [2]SD.Ayesha Farhana

[1]Professor of ECE Department, [2]Student,
Department Of Electronics and Communication Engineering,
Jawaharlal Nehru Technological University, Kakinada, India

Abstract: **Gaussian process regression (GPR) is mostly widely used now-a-days for obtaining super resolution of an image but its applicability is limited by its computational cost when large number of examples are needed. In order to alleviate this problem a novel example learning based SR method called active-sampling Gaussian regression(AGPR).In this method in order to select more informative samples for training the regression parameters an active learning strategy is used, which shows an improvement on computational efficiency while preserving the quality of image.**

Index Terms**: Image Super-resolution, Active-sampling Gaussian process regression, reconstruction quality, performance analysis.**

1. INTRODUCTION

Estimating a High Resolution (HR) image from Low Resolution (LR) image is the main objective of Image Resolution. This concept is used now-a-days in criminal investigation, video surveillance, medical imaging etc. The existing SR approaches can be divided into 1.Interpolation based 2.Reconstruction based 3.Learning based methods.

In Interpolation-based SR methods, estimation of unknown pixels in the HR image is done by using different kernel functions. Commonly used interpolation based methods are Bicubic interpolation, linear interpolation and neighbor interpolation. However, the kernel functions used in the above interpolation approaches are isotropic, which cannot reflect the intrinsic structures of images perfectly. To overcome this, an adaptive interpolation has been proposed. Which is simple yet fast, but is prone to produce blurring details in textures and zigzagging artifacts along edges. Reconstruction-based SR methods are based upon image degradation model and solve an ill-posed inverse problem of de-blurring, up-sampling, and de-noising for a high-quality image. Learning-based SR approaches can be further grouped into two sub-categories: coding-based methods and regression-based methods.

In Coding-based method, it is assumed that the LR feature space and the corresponding HR feature space share the same representation over their own databases, by which the coding relationship between LR feature spaces is applied to the HR feature space for detail synthesis. Coding-based SR algorithms include neighbor embedding, over-complete dictionary-based and orthogonal dictionary-based sparse coding, etc. Regression-based methods utilize various regression models or machine learning techniques to learn the mappings from the LR feature space to the HR one, such as MRF, kernel ridge regression, linear regression, neural network, support vector regression (SVR), and Gaussian process regression (GPR).

Recently, the GPR has attracted more attention in the SR literatures due to its interpretation and nonlinear mapping capability. For example, He et al. proposed a two-step SR framework (first up sampling and then de blurring) based on the GPR. Despite its effectiveness, the computational efficiency of GPR may tremendously decrease when some special learning tasks such as example learning based SR which needs millions of examples for a competitive result. As a result, a large training dataset is not propitious to both running time and memory allocation. .

To overcome this drawback, a novel learning-based SR method called active-sampling Gaussian process regression (AGPR) is proposed by employing active learning strategy to extract more informative samples from a large training dataset, which can overcome the bottleneck of the GPR when computing the inversion of covariance matrix.

II.PROPOSED METHODOLOGY

Main contribution of the proposed method is as follows:

1) Active learning method is applied to GPR-based SR, which can significantly reduce the cost at the same time preserves the quality of the image.

2) In order to surmount the complexity, a pre-learned projection matrix is used in the GPR which boosts the run time.

3) The efficiency of proposed method is discussed in terms of performance parameters

Compared with the traditional random sampling, active sampling is beneficial to extract more informative samples.

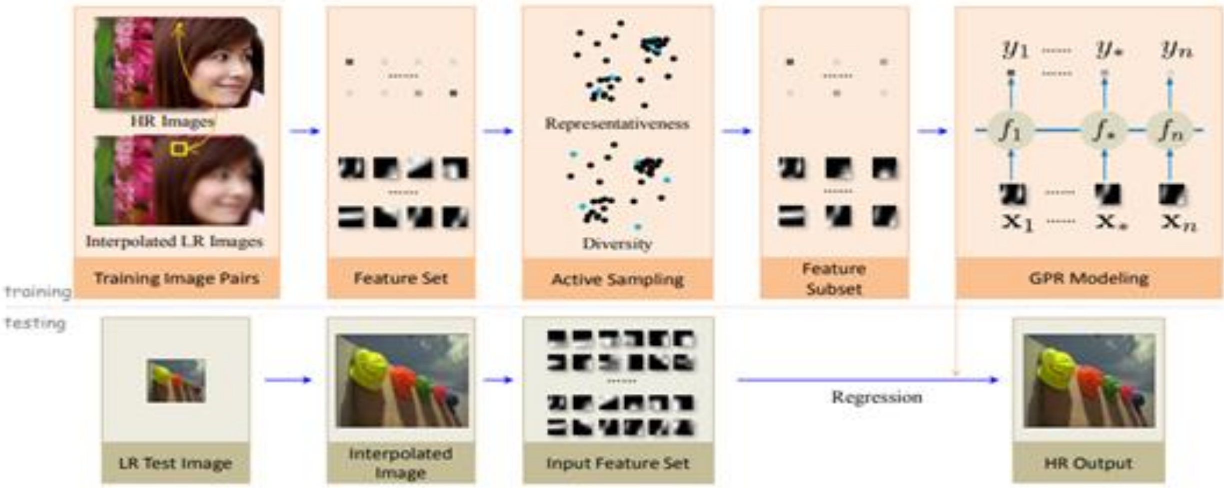

Fig.1. Block diagram for Improving Resolution using AGPR method

III.ALGORITHM

input : (I, s, {Iq, Hq}m q=1) // I is the LR input test image, s is the scale factor, {Iq, Hq}m q=1 is the Training interpolated LR and HR image pairs
output : Final SR result SH // Training Phase
Randomly select n patch pairs {P (I) l , P(H) l } n l=1 from {Iq, Hq}m q=1;
Let D , {< xl , yl >} = {< P(I) l , cen(P (H) l) − cen(P (I) l) >}; // cen(·) returns the center pixel of a patch
Active-sampling r (r n) informative samples from D to get D0 ;
D0 = {< P(I) u , yu >} r u=1;
Training GPR model f based on D0 ;
Compute the projection matrix P , K −1 y y beforehand; // Testing Phase
Interpolate test LR image I to SI ;
Initialize SR result image SH = SI ;
for each test input patch of {x ∗ k } in SI do
y ∗ k = K(x ∗ k , X) ∗ P, where X , {P (I) u } r u=1;
y ∗ k = y ∗ k + cen(x ∗ k);
Replace the corresponding pixel in SH;
end
SH ← IBP(SH);
return SH;

For convenient expression, the boldface lowercase letters such as x and y denote column vectors, the lowercase letters such as x and y denote scalars, and the capital letters such as X and Y denote matrices or images. Fig.1. illustrates the proposed SR framework, and the corresponding pseudo-code of AGPR algorithm is summarized in Algorithm. There are two stages containing in the proposed method, namely training phase and testing phase.

In the training phase, the training HR images are first blurred and then down sampled to produce the corresponding LR images. Then the LR images are up scaled to the same size of their corresponding HR ones with interpolation. With the HR images and the interpolated image pairs, the image patches extracted from the interpolated LR images are used as the inputs of training samples and the center pixels of the corresponding HR patches from the HR images are used as the initial responses. Assuming that the responses of our GPR model are zero-mean, the center pixels of patches are taken from the interpolated LR images as the corresponding response means, and the initial responses are subtracted by their means to obtain final response.

A. Kernel Selection: In the GPR model, the covariance is evaluated by the applied kernel function. Therefore, how to select the kernel function is the key to the performance of mapping. In this paper, we integrate two kernel functions, namely linear kernel and noise kernel, for more robust SR estimation. The linear kernel is anisotropic and it enables to catch more structure similarity than the RBF kernel, because the image patches in natural images are commonly structured. The linear kernel can well reflect both positive and negative correlation of samples, which provides more structural information for prediction.

B. Hyper-parameter Learning: The objective of training GPR is to learn the optimal hyper-parameters for prediction. In this paper, we initialize the hyper-parameters according to their physical meanings. Because the interpolation image can be seen as an initial estimation of the HR image, so we use the standard deviation of residuals.

C. Iterative Back Projection Since the proposed AGPR-based SR approach is pixel-wise, the structure information of the outputs is not considered. Thus it is necessary to take iterative back projection (IBP) as the post-processing to further improve the quality of the HR images obtained by the AGPR, such that the resulting images are consistent with the input LR images via the degradation mode.

Three objective assessment indices of PSNR, SSIM, and FSIM are employed to evaluate the SR performance obtained from different methods. PSNR is defined as 10 log10(2552/MSE), wherein MSE is the mean squared error (MSE) for two monochrome images to be compared. The SSIM and FSIM index are full reference metric that is a dimensionless score ranging from 0 to 1

Quality Assessment: The objective comparison of different SR approaches is done for some benchmark test images . Each image corresponds to three lines, which are PSNR, SSIM, and NC from top to bottom, respectively. Based on the results in Table II, it is clear that the proposed method achieves the top level results in terms of three quantitative assessments.

IV.RESULTS

Fig.2..LR input image

Fig.2.2.HR output image

V.TABULAR COLUMNS

TABLE I --Objective Quality Assessment Of Proposed Method For Different Images

Image	scale	PSNR	SSIM	NC	Max Difference
Lena	X 4	74.566142	0.990417	1.000654	106
Mandril	X 4	70.147333	0.985460	1.007144	117
Hotel	X 4	73.522666	0.999594	0.994279	101
Baby	X 4	79.578123	0.996958	1.000589	88

TABLE II---Objective Quality Assessment Of different Methods

Image	scale	PSNR		SSIM		NC		Max Difference	
		RFI	Proposed	RFI	Proposed	RFI	Proposed	RFI	Proposed
Lena	X 4	72.58757	74.566142	1.012220	0.990417	0.987366	1.000654	130	106
Mandril	X 4	67.49913	70.147333	1.011620	0.985460	0.974030	1.007144	200	117
Hotel	X 4	70.937006	73.522666	1.013638	0.999594	0.982528	0.994279	158	101
Baby	X 4	77.7044	79.578123	1.003128	0.996958	0.997014	1.000589	96	88

VI.CONCLUSION

This paper presents a novel AGPR-based SR method by integrating active-sampling scheme to improve the performance of the traditional GPR-based SR approach. With active-sampling, more informative samples can be selected to train the GPR model, which can reduce the computational complexity while improving the reconstruction quality. Moreover ,a universal pre-learned projection matrix is used to surmount the difficulty of computing the projection matrix for the inputs online which showed the effectiveness of the proposed SR method.

Acknowledgment

Deadlines play a very important role in successful completion of project on time, efficiently and effectively .I convey my regards and thanks to my Guide Prof.Dr.I.Santhi Prabha for constantly monitoring me towards the development of the project and setting precise deadlines.

REFERENCES

[1] R. G. Keys, “Cubic convolution interpolation for digital image processing,” IEEE Trans. Acoust., Speech, Signal Process., vol. ASSP-2, no. 6, pp. 1153-1160, Dec. 1981.

[2] L. Wang, H. Wu, and C. Pan, “Fast image up sampling via the displacement field,” IEEE Trans. Image Process., vol.23, no.12, pp.5123-5135, Dec. 2014.

[3]J. Sun, J. Sun, Z. B. Xu, and H. Y. Shum, “Gradient profile prior and its applications in image super-resolution and enhancement,” IEEE Trans. Image Process., vol. 20, no. 6, pp. 1529-1542, Jun. 2011.

[4] K. Zhang, X. Gao, D. Tao, and X. Li, “Single image super-resolution with non-local means and steering kernel regression,” IEEE Trans. Image Process., vol. 21, no. 11, pp. 4544-4556, Nov. 2012

[5]H. Takeda, S. Farsiu, and P. Milanfar, “Kernel regression for image processing and reconstruction,” IEEE Trans. Image Process., vol. 16, no. 2, pp. 349-366, Feb. 2007.