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SUPER RESOLUTION USING ACTIVE SAMPLING

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Abstract*— *Super Resolution (SR) is a class of techniques that increases the resolution of an imaging system. Super Resolution produces a detailed, realistic output image. The primary goal of image SR is to generate a high resolution (HR) image from one or multiple low-resolution (LR) input images. Image super-resolution is widely used in many practical applications such as satellite and medical imaging, where the analysis or diagnosis from low-resolution images can be difficult Gaussian process regression (GPR) has been successfully applied to example learning-based image super-resolution (SR). The GPR has attracted much more attention in the SR literatures due to its intuitive probability interpretation and nonlinear mapping capability. Contempt its effectiveness, the competence of a Gaussian process regression (GPR) model is finites by its remarkably computational cost when a maximum number of examples are available to a learning task. For this purpose, we palliation this problem of the GPR-based SR and propose a novel example learning-based SR method, called active-sampling GPR (AGPR).

The freshly proposed approach employs an active learning strategy to heuristically select additional informative samples for training the regression parameters of the GPR model, which shows significant improvement on computational capability while conserving higher quality of reconstructed image. The Active Sampling Gaussian Process Regression (AGPR) System selects more informative samples for training the regression parameters of the AGPR model which is applied on an interpolated image improving the efficiency. This model also provides sharper edges and finer details .Finally, we advise an accelerating scheme to decreases the time complexity, space complexity of the proposed AGPR-based on SR by using a pre-learned projection matrix.

Keywords*— *Active learning sampling, Gaussian process regression, GLCM algorithm, super resolution.

I. INTRODUCTION

Today, there is an enhancing demand for high resolution images in many fields such as criminal investigation, digital entertainment, medical industry, video surveillance, digital photography etc. By using this system high resolution images is possible because the main purpose of this system is converts the low resolution images into high resolution once, using machine learning approach to study pattern relationship and active sampling to select diverse patterns.

For complex robots such as humanoids or light-weight arms, it is often difficult to analytically model the system sufficiently well and, thus, modern regression methods can offer a viable alternative [1] [2]. SR are techniques that construct high-resolution (HR) images from many observed low-resolution (LR) images, thereby enhancing the high frequency components and removing the degradations caused by the imaging process of the low resolution camera. An attentively related technique with SR is the single image interpolation approach, which can be also used to enhance the size of image. Since there is not additional information provided, the quality of the single image interpolation is in limited due to the ill-posed nature of the problem, and the lost or decrease frequency components cannot be recovered. The based on Interpolation, SR methods typically useful various kernel functions to estimate the unknown pixels in the High resolution (HR) grids. The Bi-cubic interpolation, linear interpolation are mainly used in interpolation-based methods [3]

For grate user experience and clear visualization, a system must be developed for gaining higher resolution images from lower ones. Images comprises of distortions such as noise, artifacts, missing pixels and so on which needs to be eliminated for a usable useful image. The purpose is to develop an application which will increases the quality of image from low resolution to high resolution and remove the distortions. A sparse representation for every patch of low resolution input is acquired and the coefficient of this representation is used to produce high resolution output. The proposed framework in [4].introduces Non-local Auto-Regressive Model (NARM) taken as data fidelity term in Sparse Regression Model (SRM). The dictionary for LR and HR images are trained simultaneously deriving the similarity of sparse representation between the image patch pair with respect to their own dictionary. The LR image patch is mapped with HR image patch to produce a high resolution image patch thus resulting in HR image output. The paper [5] uses a framework for single image super resolution using sparse regression. The mapping is done from input LR images to target HR images based on example pairs of input and output images Up to date, maximum number of learning based SR approaches have been developed and they can yield assuring results. However, the state-of-the-art learning based super-resolution methods are typically non-probabilistic and can predict the high-resolution pixel values build directly provide an approximation of uncertainty. Gaussian Process Regression (GPR) in [6], performs soft clustering of pixels based on their local structure. This framework reversely maps the LR image to the corresponding HR image pixel-wise based on the local structure defined by the neighbours of each pixel.

II. RELATED WORK

Generally, the state-of-the-art SR techniques can be categorized into three classes: the interpolation based methods, the reconstruction based methods, and the learning based methods [7-10]. This paper proposes a system for converting a low resolution image into a high resolution image based on example based learning approach. The Regression based methodology has been adapted by the above approach to regressively derive the relation between the low resolution and high resolution image present in the database. This relationship among the pixels is determined based on Representativeness and Diversity. Representativeness represents bunch of pixels which results in more informative samples, while diversity defines a measurement parameter to catch the structure and informative patterns in natural images. This paper also introduces Active learning scheme to improve the performance of the traditional SR-GPR based super resolution approach by heuristically selecting more informative samples for training the regression parameters of the GPR model. This methods apply various smoothness priors and impose the constraint that makes the HR image reproduce the original LR image when properly down sampled. Therefore, the performance of these methods relies on the prior information and the compatibility with the given image.

III. ARCHITECTURAL DESIGN

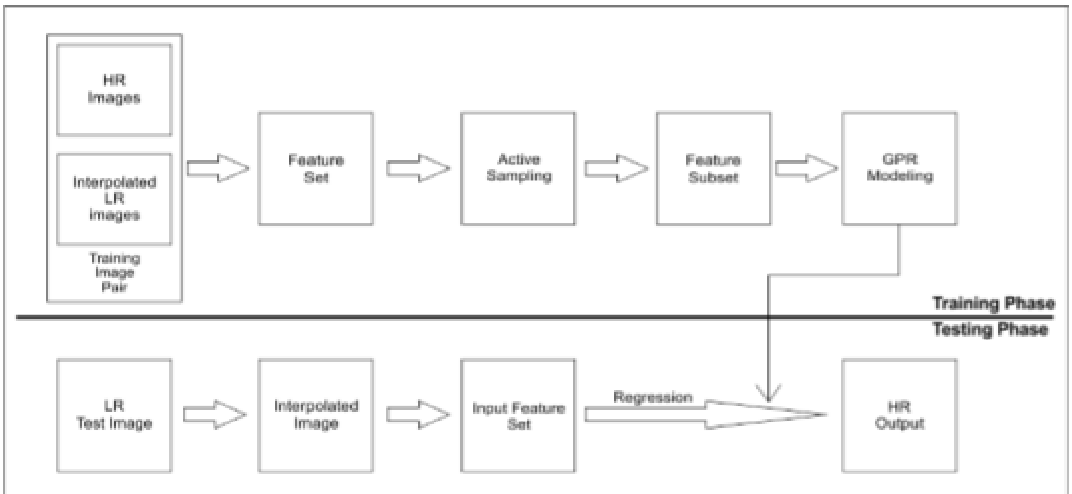

Fig: AGPR Model Framework.

1. Training Phase: The Image pair used in the training phase consists of High Resolution image and Low Resolution image. The LR image is the interpolated version of the same HR image i.e. the images belong to the same scene. Then the Feature set is extracted for this pairs of images. The LR images are classified under positive category and the HR images under negative category. Then all the positive and negative category images are combined and provided to WEKA as an input. Then further active sampling is carried out on the combined set of positive and negative category images, for getting more précised samples.

2. Testing Phase: A query LR image is given as input on which pre-processing is done. Then the feature set is generated for the query test image and based on the category it belongs to enhancement is done on the image, for getting HR image.

3. Feature Set: Feature extraction in done using GLCM (Grey Level Co-occurrence Matrix) algorithm. Various features such as energy, contrast, co-relation, homogeneity of the pixels are calculated and values for the same are derived forming the base of the feature extraction module.

4. GPR Modelling: The pattern relation is derived using the GPR modelling. This relationship is formed from the feature subset derived using feature extraction algorithm and further applied on the feature set of the input interpolated low resolution image.

5. GLCM Algorithm: The Grey-Level Co-occurrence Matrix (GLCM) is a statistical technique for feature extraction. The goal is to provide an unknown sample image and extract features, which can be in scaler numbers, discrete histogram or empirical distribution. There are total fourteen features: Angular Second Moment, Contrast, Correlation, Sum of Squares or variance, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information measure of correlation, energy, homogeneity. Out of these fourteen features, four features are selected for further processing.

Energy: Energy means uniformity. The formulation of energy is:

$$Energy = \sum_{i,j=0}^{N-1} \left(P_{ij}\right)^2$$

Entropy: Entropy is the measure of randomness of the intensity image. The formulation of entropy is:

$$Entropy = \sum_{i,j=0}^{N-1} -\ln(P_{ij})P_{ij}$$

Contrast: Difference in maximum and minimum intensity of the image. Formulation is as follows:

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij}(i-j)^2$$

Correlation: Measures how correlated a pixel is with its neighbouring pixel.

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2}$$

Where,

P_{ij}=Element i,j of the normalized symmetrical GLCM.

N= number of grey level in the image.

$$\mu = \sum_{i,j=0}^{N-1} iP_{ij}$$

μ=GLCM mean; calculate as

σ^2= *the variance*

$$\sigma^2 = \sum_{i,j=0}^{N-1} P_{ij}(i-\mu)^2$$

IV. CONCLUSION

The system is helpful in conversion of low resolution image into high resolution using active sampling and Gaussian process regression modelling. The project is based on machine learning based regression methodology which represents the relation between the images in training phase and applies it on the input given to the system in testing phase. The feature set is extracted using feature extraction algorithm and further sampled using active sampling. The feature subset consisting of sampled features, is processed using GPR model and a valid pattern relationship is derived. The above relation is then applied on the query low resolution image to generate high resolution output.

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