HYBRID APPROACH FOR IMAGE SUPER RESOLUTION USING SPARSE

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Abstract: Recently Learning –Based Approach for Super –resolution (SR) has been used which generates 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 is 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 pair-wise patches from training database instead of all the training data. The experimental result shows that it achieves three times better quality of image than other Using proposed model with machine learning. Use sparse dictionary base approach for remove low resolution patch and replacement with high resolution patch using dictionary base approach and also prove result using PSNR, SSIM parameters.

***IndexTerms* - Super-resolution, Sparse Dictionary, Interpolation, Bi-cubic Interpolation, machine learning**

I. INTRODUCTION

Image processing is a process of taking an image as an input and performs some operations on it, in order to manipulate the image which includes enhancing, reducing rotating etc. or extracting some useful information from it and producing the desired output [8]. To enhance the image resolution is most important in the field of image processing. A common Resolution Enhancement (RE) technique is to vary the size of dots like pixels. Image resolution is the detail an image holds [10]. In most digital imaging applications, high resolution images or videos are usually desired for later image processing and analysis. The desire for high image resolution stems from two principal application areas: improvement of pictorial information for human interpretation; and helping representation for automatic machine perception. Image resolution describes the details contained in an image, the higher the resolution, and the more image details. The resolution of a digital image can be classier in many different ways: pixel resolution, spatial resolution, spectral resolution, temporal resolution, and radiometric resolution [9].

Super resolution is a method for reconstructing a high resolution image from several overlapping low-resolution images. The low resolution input images are the result of re-sampling a high resolution image. The goal is to find the high resolution image which, when re-sampled in the lattice of the input images according to the imaging model, predicts well the low resolution input images. [11].

1.1 Related Work

A. Interpolation:

Interpolation means to interpolate the missing pixels value into the image and create high resolution image for some specific application. In other words, Interpolation is a technique for achieving new unknown pixel values within the range of discrete known pixel values [12]. Compared with other approaches, this method keeps the most simple calculation procedure and the minimum computation complexity. Actually, image interpolation is an essential operation technique in most image processing field, which is mainly utilized for image resizing. Classical interpolation based methods have the following three ways [15]

Table 1 Interpolation Methods [15]

Methods	**Advantages**	**Disadvantages**
Nearest neighbor Interpolation	Simple and easy to implement	Doesn't have sub-pixel accuracy
Bilinear Interpolation	Provide better result than nearest neighbor method	Creates the artifacts and poor preservation image detail
Bicubic Interpolation	Most popular and basic method used in SR methods, provide better smoothness, fast computation	It created jaggy effect because of the negative lobs of Bicubic interpolation function

B. Sparse Dictionary:

Sparse representations of signals have received a lot of interests in recent years. Sparse representation is exploited to give the most compact representation of a signal. Any signal can be represented as a linear combination of atoms in an over complete dictionary. Recent developments in multi-scale and multi-orientation representation of signals are an important incentive for the

research on the sparse representation. Different dictionary learning algorithms such as matching pursuit, orthogonal matching pursuit, method of optimal direction (MOD) or k-singular value decomposition (k-SVD) are extensively popular in the literature. Sparse representation have been exploited for various applications such as signal separation, denoising, classification, image in-painting and reconstruction [16].
Here this are the methods of sparse dictionary can be described below:

1. **Method of Optimal Direction (MOD):**

Above problems can be posed as a nested minimization problem: an inner minimization of the number of nonzero in the representation vectors X_i, for a given fixed D and an outer minimization over D. A strategy of alternating minimization thus seems very natural. At the k-th iteration, we use the dictionary $D_{(k-1)}$ from the k-1 th step and solve M instances of entry y_i, and each using the dictionary $D_{(k-1)}$. This gives us the matrix $X_{(k)}$, and we then solve for $D_{(k)}$ by Least-Squares [16].

$$D_{(k)} = \arg_D \min \left\| Y - DX_{(k)} \right\|_F^2 \quad (1)$$
$$= YX_{(k)}^T \left(X_{(k)} X_{(k)}^T \right)^{-1} \quad (2)$$
$$= YX_{(k)}^+ \quad (3)$$

Where $X_{(k)}^+$ is the pseudo-inverse.

2. **K-singular value decomposition (k-SVD)**

The sparse representation problem can be viewed as a generalization of the Vector Quantisation objective function, in which we allow each input signal to be represented by a linear combination of code words. In dictionary learning, dictionary atoms are the analogical to the code words. Now, coefficients vector can have more than one nonzero entry and arbitrary values. The objective problem for k-SVD dictionary learning is [16]:

$$\min_{D,X} \|Y - DX\|_F^2 \quad \text{subject to} \quad \|X_i\|_0 \leq k_0 \quad \forall i \quad (4)$$

Where $Y = \{y_i | \text{ i in } [1,K], y_i \in R^n\}$ and X is formed by column stacking all vectors X_i and $\|\|\|_F^2$ denotes the Frobenius norm square [20].

3. **Orthogonal Matching Pursuit (OMP)**

The Orthogonal Matching Pursuit (OMP) algorithm is a greedy algorithm with attempts to find a sparse representation of a signal given a specific dictionary. The algorithm attempts to find the best basis vectors iteratively and each iteration present the error in representation is reduced. This achieved by selection of that atom from the dictionary which has the largest absolute projection on the error vector. This essentially implies that we select that atom, which adds the maximum information and hence maximally reduces the error in reconstruction. Given a signal vector y and a dictionary D the algorithm attempts to find the code vector x in three steps [16]

- Select the atom which has maximal projection on the residual
- Update $X^k = argmin_x^k \|y - DX^k\|_2$
- Update the residual $r^k = y - y^k$

C. Machine Learning:

Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning focuses on the development of computer programs that can access data and use it learn for themselves. The process of learning begins with observations or data, such as examples, direct experience, or instruction, in order to look for patterns in data and make better decisions in the future based on the examples that we provide. The primary aim is to allow the computers learn automatically without human intervention or assistance and adjust actions accordingly [13].

Types of ML:

1. **Supervised learning**

Supervised learning can be defined as "Training data includes desired outputs". Supervised learning is the Data mining task of inferring a function from labeled training data. The training data consist of a set of training examples. In supervised learning, each example is a pair consisting of an input and a desired output value. Supervised machine learning systems provide the learning algorithms with known quantities to support future judgments. Detecting Diseases (Medical Treatment), Chat-bots, self-driving cars, facial recognition programs, expert systems and robots are among the systems that may use either supervised or unsupervised learning. Supervised learning systems are mostly associated with retrieval-based AI but they may also be capable of using a generative learning model [14].

2. **Unsupervised learning**

In Unsupervised Learning the "Training data does not include desired outputs". Unsupervised learning is the training of an artificial intelligence algorithm using information that is neither classified nor labeled and allowing the algorithm to act on that information without guidance. AI systems capable of unsupervised learning are often associated with generative learning models, although they may also use a retrieval-based approach (which is most often associated with supervised learning).

Unsupervised learning algorithms can perform more complex processing tasks than supervised learning systems. However, unsupervised learning can be more unpredictable than the alternate model [14].

3. Semi-supervised learning

Semi Supervised learning contains the "Training data includes a few desired output. Semi-supervised learning is a class of machine learning tasks and techniques that also make use of unlabeled data for training – typically a small amount of labeled data with a large amount of unlabeled data. Semi-supervised learning falls between unsupervised learning (without any labeled training data) and supervised learning (with completely labeled training data) [14].

4. Reinforcement learning

Reinforcement Learning rewards from sequence of actions. Reinforcement Learning is a type of Machine Learning, and thereby also a branch of Artificial Intelligence. It allows machines and software agents to automatically determine the ideal behavior within a specific context, in order to maximize its performance [14].

II. LITERATURE SURVEY

2.1 Relevance Survey on Image Super-Resolution

This paper [1] Super-resolution reconstruction technique reconstructs low-resolution images into the high-resolution images by using image pixels displacements. Super-resolution reconstruction technology is an effective means to enhance the resolution of satellite video images. Interpolation reconstruction method obtains more accurate interpolating functions by increasing the pixels of neighborhoods. It can reconstruct video images, and the quality evaluation combines the subjective evaluation with objective evaluation. The static feature edges reconstructed by Interpolation reconstruction method even more smooth and clear which can improve the resolution of video images.

In this paper [2] they propose a novel super pixel segmentation approach based on a distance function to design the balance among boundary adherence, intensity homogeneity, and compactness characteristics of the resulting super pixels. The expected number of super pixels the segmentation based method begins with initializing the super pixel seed positions to obtain the initial labels of pixels. Here they optimize the super pixels iteratively based on the defined distance measurement.

This paper [3] proposed method will reconstruct HR images by using HR images reconstruction. The computational complexity is higher than those non-iterative methods such as SRCNN and FSRCNN methods. This hybrid parametric sparse model learning method is proposed for image super resolution. For the sparse codes of the HR patches are learned the training set data.

In this paper [4] they propose a novel hyper-spectral image super-resolution method via self-similarity constrained sparse representation. They explore the similar patch structures across the whole image and the pixels with close appearance in local regions to create global structure groups and local-spectral super-pixels. Also proposed a global-structure and local-spectral constrained sparse representation for hybrid fusion based HS image super-resolution.

This paper [5] proposes to construct an appropriate dictionary without using sample image set, and a new super resolution algorithm is proposed. They compare the proposed algorithm with the Bicubic interpolation method and the TV regularization. In this paper they proposed a super pixel segmentation technique to restore the high quality of data efficiently. A study of the dictionary learning based super-resolution algorithm achieves a high performance. The dictionary learning based algorithm often demands the sample image set to construct the dictionaries, and the performance of the algorithm depend heavily on the sample image set.

In paper [6] propose an image quality enhancement method to improve the objective quality of GAN based super-resolution method. The SRGAN generated image as style image, and another resolved image with high objective quality as content image. Also they use the image style transfer algorithm to fuse them to generate an image with high objective and perceptual quality simultaneously.

In this paper [7] they focus is on enhancement of spatial resolution. Captured image using low resolution camera is degraded due to aliasing, blurring and addition of noise. The most obvious solution is increase in pixel density of sensors so that we can capture high resolution image directly. But due to physical constraints on imaging devices, the pixel size cannot be decreased beyond certain limit. Original image is passed through the wavelet based model followed by the adaptive filter which will produce Super Resolved (SR) image with high visual quality.

2.2 Comparative Study

Table 2 Comparison table of literature survey

Sr.No.	Title	Methodology
1	"Super-Resolution Reconstruction of Satellite Video Images Based on Interpolation Method" [1]	Motion Estimated Methods, Interpolation reconstruction, Vandewalle(motion estimation), quality evaluation
2	"A Simple Algorithm of Super-pixel Segmentation With Boundary Constraint" [2]	Graph-Based Methods, Gradient Ascent Methods, K-Means-Based Methods

3	"Image Super-Resolution With Parametric Sparse Model Learning" [3]	sparse model, Sparse codes learning algorithm
4	"Self-Similarity Constrained Sparse Representation for Hyper-spectral Image Super-Resolution" [4]	ADMM, HIS SR, state of art
5	"Single-frame Super-resolution Using Super-pixel Based Dictionary" [5]	Dictionary learning based algorithm
6	"Enhancing Image Quality via Style Transfer for Single Image Super-Resolution" [6]	SISR algorithms, MSE loss based methods, Perceptual loss based methods
7	"Single Image Super Resolution using Sub-band Coder and Adaptive Filtering" [7]	Discrete wavelet transform (DWT), Redundant Wavelet Transform (RWT), Normalised Least Mean Square (NLMS) algorithm

III. PROPOSED MODEL

3.1 Proposed System

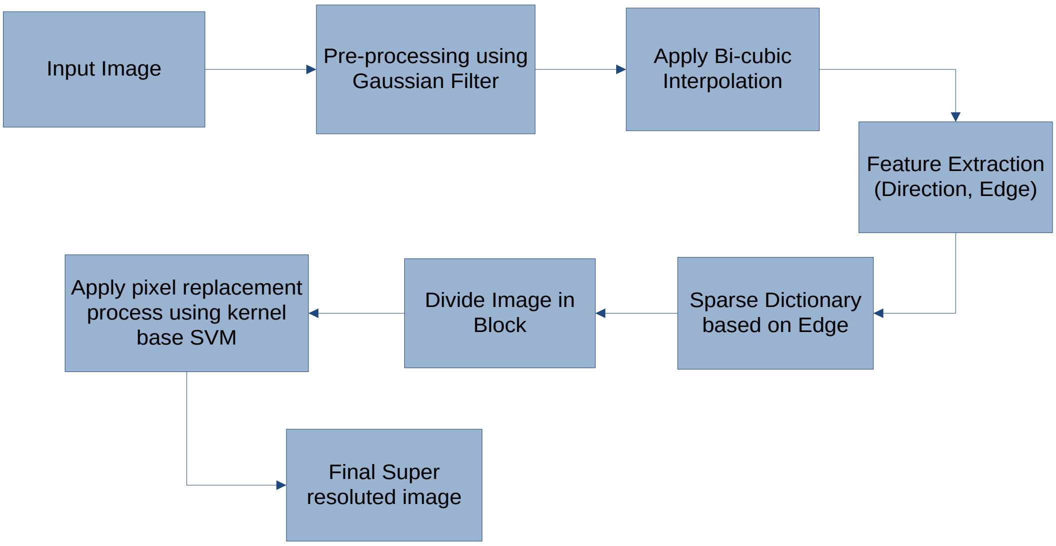
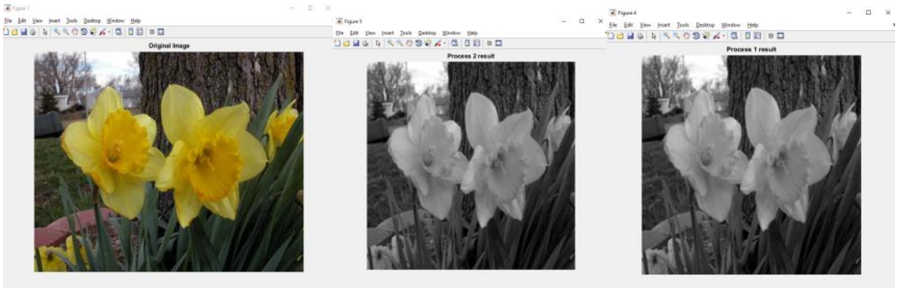


Fig. 1 Proposed System

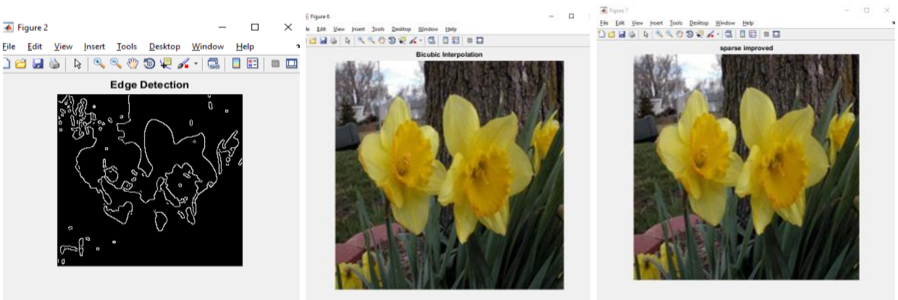
IV. IMPLEMENTATION RESULTS

4.1 Using Flowers Image Dataset implementation steps screenshots are given below:

Results of Image 1 Data:



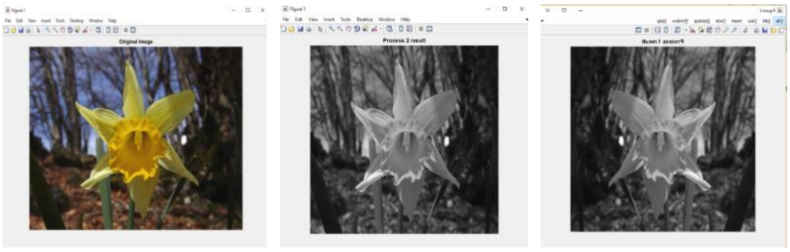
(a) Original Image (b) Gaussian Filter (c) Interpolation Image



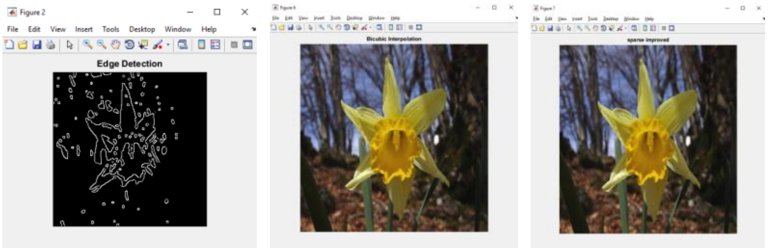
(d) Edge Detected Image (e) Bicubic Interpolation Image (f) Sparse Improved Image

Fig. 2 Image screenshots of Sparse Improved step-wise Data

Results of Image 2 Data:



(a) Original Image (b) Gaussian Filter (c) Interpolation Image

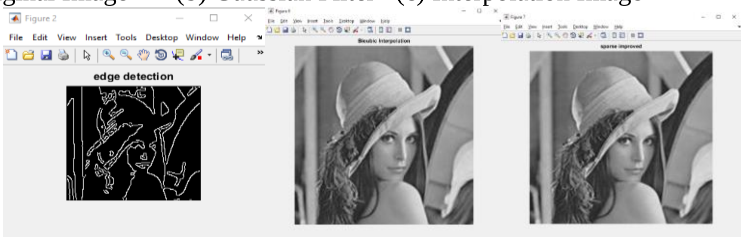


(d) Edge Detected Image (e) Bicubic Interpolation Image (f) Sparse Improved Image

Fig. 3 Image screenshots of Sparse Improved step-wise Data

4.2 Using Basic Lena Image, implementation step screenshots are given below:

(a) Original Image (b) Gaussian Filter (c) Interpolation Image



(d) Edge Detected Image (e) Bicubic Interpolation Image (f) Sparse Improved Image

Fig. 4 Basic Lena trained Image Screenshots

4.3 Parameters Result:

Table 3 Parameters Result

Parameters Value				
Images	**PSNR**	**SSIM**	**FSIM**	**Elapsed Time**
Image 1	42.5113	0.9803	0.9984	4976.756946 seconds
Image 2	44.0311	0.9856	0.9986	5310.964269 seconds
Image 3	43.3930	0.9810	0.9980	5355.627100 seconds
Image 4	45.0531	0.9900	0.9985	5154.641992 seconds

V. CONCLUSION

In these research work, we design hybrid approach for super image resolution using machine learning to solve the current issue resulted to resolution, time complexity and robustness. So using proposed approach improves quality of low resolution image and convert image in super resolution image and improve result with SSIM and PSNR parameters.

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