Proceedings of the International Conference on Intelligent Sustainable Systems (ICISS 2017)
IEEE Xplore Compliant - Part Number:CFP17M19-ART, ISBN:978-1-5386-1959-9

Single Image Super Resolution: An Efficient Approach using Auto-learning and Filter Pooling

Greeshma M. S.
School of Computer Sciences
Mahatma Gandhi University, Kottyam, Kerala
greeshmams.r@gmail.com

Bindu V. R.
School of Computer Sciences
Mahatma Gandhi University, Kottayam, Kerala
binduvr@mgu.ac.in

***Abstract*— Stimulated by recent approaches on internal database driven image super resolution, we propose a super resolution algorithm based on auto learning and filter pooling approach. This paper presents an algorithm where auto-trained high frequency cluster of patches are used to reconstruct a high resolution image. The auto-trained features are extracted using filter pooling approach combining the advantages of Sobel and Gabor filters. The key feature of this approach is preserving features at different frequencies with different orientations using self-similarity to avoid the use of multiple images. The experimental analysis shows that the proposed technique gives better results when compared to existing state-of-the-art internal database methods for image super resolution in terms of quantitative and qualitative performance measures.**

Keywords*— *Auto-training, super resolution, filter pooling, high frequency cluster, Gabor filter

I. INTRODUCTION

As there is an increase in demand of high resolution images in various fields of application recently super resolution technology is one of the algorithmic techniques for generating high resolution images. Single Image Super Resolution (SISR) techniques are used to create a high resolution image I_{HR} from the input low resolution image I_{LR}. The internal driven database exploits learning algorithms for image super resolution without the support of external example library. The SR approach is established by the self-similarity property, whereby trivial patches of images occur frequently at different scales in a similar image. Single image super-resolution utilizing traditional methodologies, for example, interpolation techniques or reconstruction based methods demonstrate undesired objects and over smoothing in the reconstructed HR image, particularly along image boundaries. In a self-trained environment, correlation between image patches is maintained across different image scales and can be represented as

$$\rho I_{i1}(xj), \rho I_{i2}(x_j) \ldots\ldots\ldots\ldots \rho\, I_{in}(x_j) \quad (1)$$

where ρ denotes the relationship between image patches across the different scales $I_{i1}.I_{i2}\ldots\ldots I_{in}$, the upsampled versions of the input image and $\rho I_{ii(xj)}$ indicates the relationship between image patches(x_1, x2..) at the i^{th} scale. The intention of super resolution is to preserve correlation between image patches at different scales. A fast and efficient auto-learning based image super resolution algorithm has been proposed here, which enables self-trained features to be used to reconstruct the HR image I_{HR}. The method is computationally fast compared to other algorithms. The process is essentially relying on input image itself without using any external example library. The proposed method is applied to the single input image and maintaining correlation between image patches from various image scales, preserving local edge structures and improving visual quality are the challenging tasks.

II. RELATED WORKS AND PROBLEM CONTEXT

The internal database based super resolution techniques exploit the image self-similarity property, which illustrate that the patch contents of a natural image reappear within and across scales of the same image [1] and [2]. Singh et al. employs self-similarity postulate for super-resolving noisy images. In Michaeli and Irani [3] usage of blur kernel expresse the recurrence of small patches. Yang et al., [4] demonstrates the first order regression and incorporates local self-similarity to perform super resolution. Yang et al. [5] also exploits patch self-similarity within the image and requires sparsity information to regularize reconstruction process. Zhu et.al introduces a SISR algorithm based on deformable patches based method, and applies numerous deformed patches arrangement for the final reconstruction process [6]. Zhu et al. extends the deformable patches based prototype to be analyzing in gradient domain and promote a deformable compositional model to modularize the non-singular structures into singular structures [7]. Ahuja et al. offers a modularization of geometric patch transformation model into perspective distortion to supervising structured scenes [8]. Chris Damkat [9] introduces a SISR algorithm according to self-examples and texture synthesis, and its performance is extremely dependent on contents of an image. [10] Proposes the back projection procedure to estimate the HR image. It requires a content-adaptive bilateral filtering in primary computation to support the edges and a content-adaptive nonlocal means filtering to generate the final result and also exploits self-similarity acquired from the single LR image [16]. However, one of the drawbacks of nonlocal means filtering is that it tends to over smoothen images there by losing the edge features. In current times stated Nonlocal Autoregressive Model (NARM) algorithm presents local and non-local redundancies in images, integrating the image nonlocal self-similarity into conventional Sparse Representation Model (SRM) to regularize solution [16]. But one of the faults of NARM is that the algorithm is not powerful when there are no enough monotonous patterns in the image. The above mentioned self-similarity super resolution techniques have many drawbacks, so an efficient method has been proposed. Furthermore, our proposed internal database method does not require pool of training data, and we require the assumption of image patch self-similarity in our framework.

In this paper, a new auto-learning technique for single image super resolution has been proposed, which uses auto-learning based self-trained features to reconstruct the HR image, avoiding the need for an external database. This proposed single image super- resolution algorithm uses self-examples and high frequency layer features to provide improved visual quality and better edge preservation than the results reported in the literature.

Single image super-resolution plays a significant role in many computer vision applications wherever only one LR image is available. The majorities of existing single image SR algorithms utilize an external example library and is very difficult in term of time as well as in memory complexities and the performance of them is highly dependent on the database used. The proposed approach uses only auto-trained high frequency layer, without any external databases, and hence complexities are reasonably low. The preservation of information contents of an image and visual quality improvement are two challenges in single image super-resolution. The proposed method overwhelms these two difficulties successfully, using auto-trained high frequency clusters. By adopting such an approach, information contents of an image are preserved without use of external database.

The proposed system has two contributions, firstly the strategy concentrates on the learning of proper SR models from various image scales while producing higher resolution images, and thus our approach does not search for similar image patches from the input for SR reconstruction. This avoids the difficulty of insufficient self-similarity of patches from different training images within the image of interest [1]. Secondly, the combination of Sobel and Gabor filter is used to extract Features of Interest (FoI's) from the images. This approach is named as filter pooling approach. After applying the filter pooling technique to construct a high frequency cluster, effective matching scheme is used to replace distorted patches with high frequency patches. The aforementioned technique accelerates the learning and reconstruction processes of SR images, which makes the SR with larger magnification factors computationally feasible.

III PROPOSED AUTO-LEARNING IN SINGLE IMAGE SUPER RESOLUTION

The proposed auto-learning approach uses auto-trained high frequency cluster of patches to construct high resolution I_{HR} image. The self-trained/ auto-learned features are used to generate high frequency cluster of patches from the given low resolution I_{LR} image. The constructed high frequency cluster is added with the HR image interpolated from the LR image to get the final HR image, replacing distorted patches with high resolution patches. Finally the image is generated by overlapping reconstructed patches. Performance enhancement of the algorithm is proved through experimental analysis. The details of the proposed method are given in the following sub-sections.

A. Conversion of RGB to YIQ colour space

In any color image, most of the high frequency components are present in the luminance component of the image. Due to this purpose, the proposed algorithm is implemented only to the luma component of the given image, for improved edge recovered capability. Consider an input LR image I, which is in RGB colour space [16]. The first phase in the proposed method is to convert the image I_{LR} from RGB colour space to YIQ as follows:

$$\begin{pmatrix} Y \\ I \\ Q \end{pmatrix} = \begin{pmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.274 & -0.322 \\ 0.211 & -0.523 & 0.312 \end{pmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (2)$$

$$I_Y = (0.299 \times I_R) + (0.587 \times I_G) + (0.114 \times I_B) \quad (3)$$

$$I_I = (0.596 \times I_R) - (0.274 \times I_G) - (0.322 \times I_B) \quad (4)$$

$$I_Q = (0.211 \times I_R) - (0.523 \times I_G) + (0.312 \times I_B) \quad (5)$$

Where I_Y is the luminance component of the LR image, I_I and I_Q are chrominance information [16]. The proposed method uses luma information I_Y to perform super resolution.

B.Auto-learning framework

The auto-trained features used in this process are high frequency cluster generated from luminance component of the LR image, and is also stimulated by the current achievement of the method of Yang et.al [5]. The image I_Y is down-scaled (↓) and consequently up-scaled (↑) using linear interpolation method by a factor of N to get an intermediate LR image I_Y, a smoothened image with high frequency details missing. The process of auto-feature generation is illustrated in Fig. 1.

$$I^Y_{LR1,2,3\ldots} = (I_{LR} \downarrow N_{1,2,..n}) \quad (6)$$

$$I^Y_{HR1,2,3} = (I^Y_{LRi} \uparrow N_{1,2..n}) \quad (7)$$

The down-sampled lower-resolution versions $\{I^Y_{LR1}, I^Y_{LR2}, \ldots)$ are interpolated to generate the corresponding higher-resolution images $\{I^Y_{HR1}, I^Y_{HR2}, \ldots\}$ using bicubic interpolation. And the remaining color channel components of the image (I^I_{HR} , I^Q_{HR}) are also generated similarly. Fig. 1 depicts the auto-learning framework with the LR-HR pairs as two image pyramids $\{ I^Y_{LR} , I^Y_{HR}\}$.

Fig. 2 demonstrates auto-learning single image super resolution applied on a Parrot LR image. Learning the spatial relationship between image patches on different scales using the features extracted from LR-HR pairs and creating an auto-trained high frequency cluster are the major operations of auto-training. The proposed method uses filter pooling approach, a combination of Sobel and Gabor filter technique is used to extract FoI's from LR-HR image scales. The Sobel filter $\{Sobel_i\}$ is used to extract accurate edge detection and also demands for preservation of edge details, and Gabor filter