Learning Based Resolution Enhancement of Digital Images

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Abstract**:** ***Image super-resolution (SR), the process that improves the resolution, has been used in many real world applications. SR is the preprocessing phase of majority of these applications. The improvement in image resolution improves the performance of image analysis process. The SR of digital images take the low resolution images as inputs. In this article, a learning based digital image SR approach is proposed. The proposed approach uses Convolutional Neural Network (CNN) with leaky rectified linear unit (ReLU) for learning and generalization. The experiments with the test dataset from USC-SIPI indicate that the proposed approach increases the quality of the images in terms of the quantitative metric peak signal to noise ratio. Further, it avoided the problem of dying ReLU.***

Keywords**:** ***convolutional neural network, deep learning, leaky ReLU, super-resolution.***

I. INTRODUCTION

Image super-resolution is the process of increasing the spatial resolution of digital images. Many practical applications prefer the high resolution (HR) images over the LR images in due to the fact that HR images possess more useful information than that of low resolution ones [1]. There are two major ways in which the resolution of digital images can be improved. The first is by making changes to the image capturing hardware modalities. Making changes to the hardware restricts the area of application. The other one is by the application of any image processing techniques. The major advantage of using image processing techniques is that they are independent of the image capturing devices. In addition to that, the resolution of low resolution images can be improved effectively by these image processing techniques, which is not realistic with the hardware changes. Image super-resolution is one of the techniques that improves the spatial resolution of low resolution images.

Over the years several SR techniques have been proposed. Each one of them are having their own advantages and limitations. This paper proposes a learning based image SR technique for enhancing the low resolution digital images in terms of resolution. The proposed approach uses CNN for learning. The leaky ReLU activation function is used. The results of the experiments have been evaluated with the quantitative measure PSNR.

The remainder of the article is organized as follows. The study about the literature on the various SR approaches are given in Section II. The proposed LSR-CLEAR approach is explained in section III. The experimental setup and the results are discussed in Section IV. The conclusion and the future scope are given in Section V followed by the list of references and the author profiles.

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II. RELATED WORKS

Several approaches have been proposed for increasing the spatial resolution of digital images over the years. The most frequently used techniques are the image interpolation techniques. For instance, nearest neighbor interpolation, bilinear and bicubic interpolations. Most of the image editing applications use bicubic interpolation to increase the resolution due to its less time complexity. However, the quality of the resultant image will be entirely dependent on the input image. The sparse coding based approaches used by the researchers produced minimal number of entries (non-zero) during the construction of high resolution images. Though it reduced the time complexity, an additional refinement process is still required in these approaches [2], [3].

The super-resolution approaches are found to be applicable invariably in all the areas of applications where the digital images can be used. These SR approaches can be classified into two large groups namely single-frame SR and multi-frame SR. The single frame approaches use a single source LR images. Whereas, the multi-frame approaches require several images of the same scene. The SR approaches are further classified in to reconstruction based approaches, which mail focus on the removal of aliasing artifacts, and learning based approaches try to formulate relationship among the low resolution and high resolution pairs of images. The reconstruction based approaches perform well when the scaling factor is below 2. The learning based approaches overcame this limitation. There have been used several methods proposed for learning the relationships among the patches. They are feature pyramid based learning, learning with belief networks, projection based learning neural networks based learning [4], [5]. The application of learning based approaches helped in generating of better HR images.

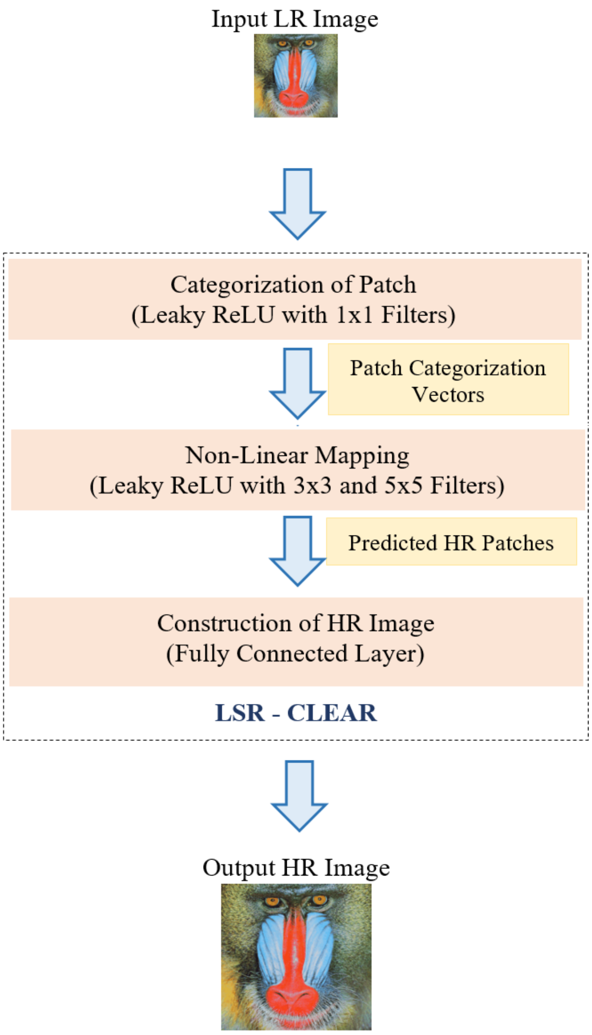


Fig. 1.Flow of LSR-CLEAR approach

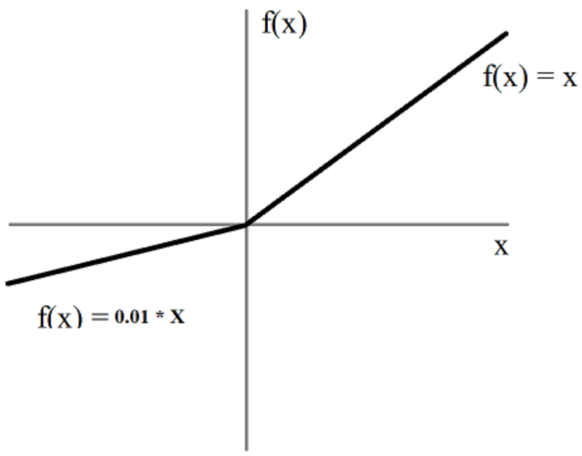


Fig. 2.Leaky ReLU

The key take away from the review is that, learning based single frame SR will result in better HR outcomes. By combining the different learning methodologies, the quality of the HR image can be improved.

III. PROPOSED APPROACH

The aim of the proposed LSR-CLEAR approach is to produce higher resolution resultant image from the low resolution input image. During the performance evaluation, the input image is taken as the reference image. The learning is achieved by the convolutional neural network. Fig.1. depicts the flow of the LSR-CLEAR approach.

The convolutional neural network in the LSR-CLEAR approach has three layers. They are, categorization of patches, non-linear mapping and construction of HR image. The first two layers use, Leaky ReLU, expressed in (1), is used as the activation function in the CNN of the LSR-CLEAR approach.

$$f(x) = x \text{ if } x \geq 0 \text{ (or) } 0.01x \text{ if } x < 0 \quad (1)$$

The major advantages of using Leaky ReLU over ReLU are that, it overcomes the limitation of dying ReLU and supports higher learning rates [6].

The filter size of 1x1 is used in the categorization of the patches. The process of patch categorization is expressed in (2). Here, f_1 is the filter of size 1x1 and b is the bias.

$$l(x) = \max(0.01x, f_1 * x + b) \quad (2)$$

The overlapping image patches are formed as the result of the non-linear mapping. Here, the proposed LSR-CLEAR approach uses the filter sizes of 3x3 or 5x5. The expression given in (3) gives the operation of non-linear mapping.

$$ll(x) = \max(0.01x, f_2 * l(x) + bb) \quad (3)$$

Here, f_2 is the filter of size 3x3 and 5x5 and bb is the bias. The final layer constructs the expected resultant HR image. It is achieved by averaging all the overlapping patches together. This averaging operation is expressed in (4).

$$h(x) = f_3 * ll(x) + bbb \quad (4)$$

Here, h(x) represents the HR image, f_3 is the filter and bbb is the bias. The LSR-CLEAR approach is an in-scale super-resolution technique that produces the HR image having the similar size as that of the input low-resolution image.

IV. EXPERIMENTAL SETUP

The proposed approach was implemented and tested with various input images taken from the USC-SIPI datasets [7] and the outputs were tabulated. Similarly, the other SR approaches such as bicubic interpolation, self-learning based SR (SLSVR) [8], sigmoid kernel SVR based SR (SKSVR) [9], deep convolutional neural network based SR (DCNN) [4] and Hybrid CNN-SVM [10] approaches were also implemented and the outputs were taken. The learned outcomes with ImageNet dataset were used for the learning [11]. The performance of the approaches is compared based on the metric PSNR.

The test images are depicted in Fig.3. The experiments were carried out for five times for each test images. The PSNR values achieved from the tests are listed in Table I.

It can be inferred from the values of Table I that the LSR-CLEAR method performs better than the existing image SR approaches. The high resolution results obtained from the SR approaches are depicted in fig.4.

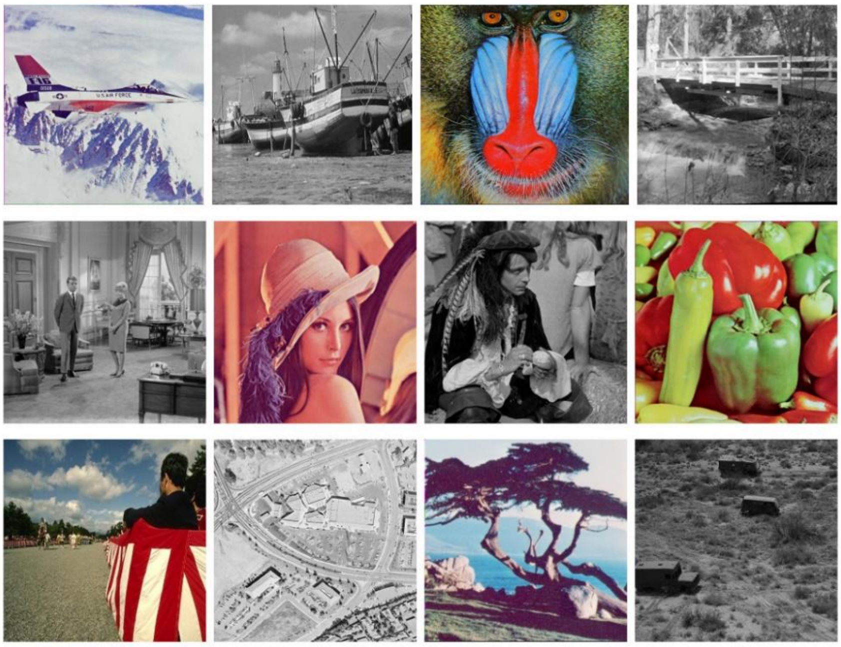
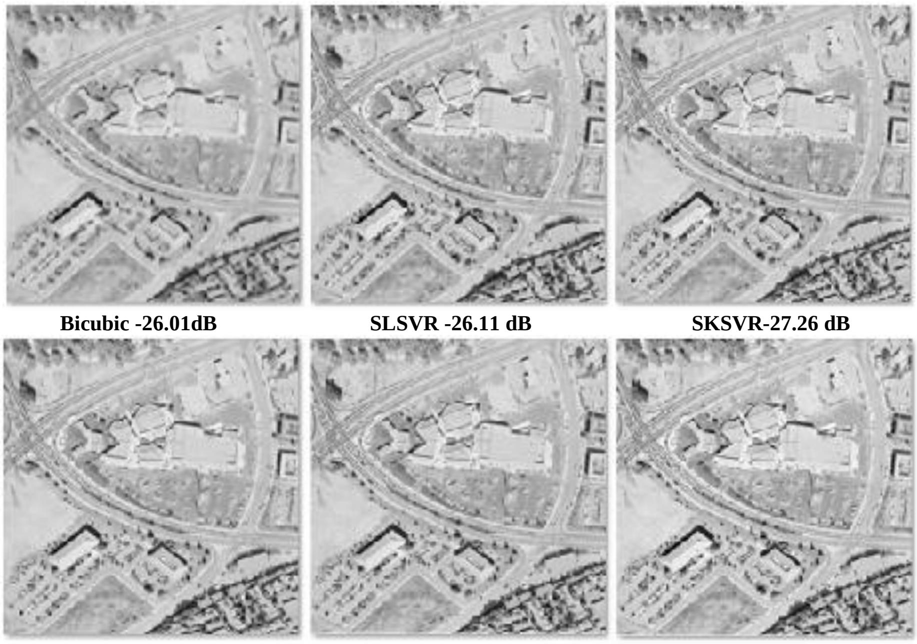


Fig. 3.Test images from USC-SIPI

Table I PSNR values (in decibels) obtained from the experiments

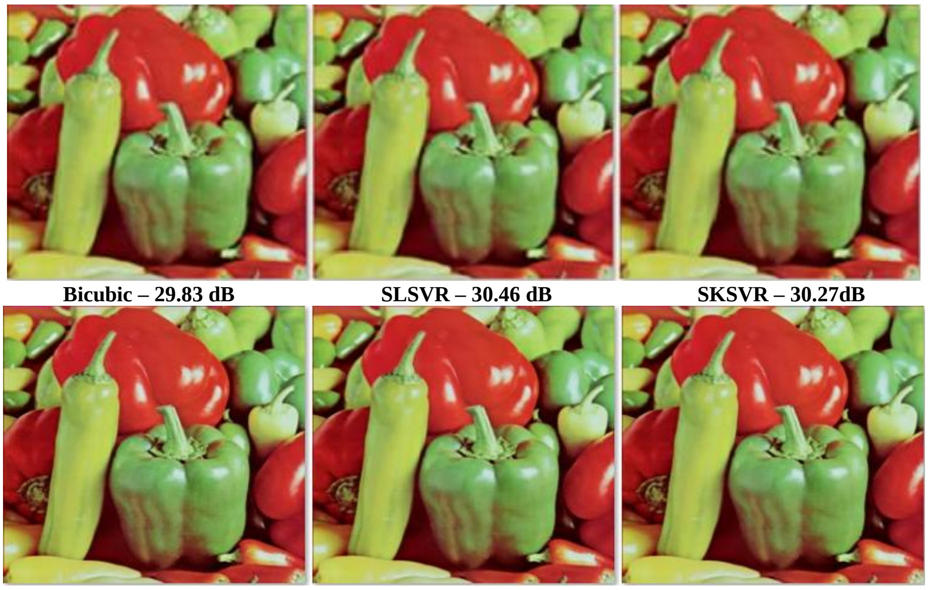
SR Methods	Bicubic	SLSVR[8]	SKSVR[9]	DCNN[4]	Hybrid CNN-SVM[10]	LSR-CLEAR
airplane	29.79	30.37	30.56	30.52	**32.22**	32.06
bluecar	27.44	27.82	27.92	28.05	28.92	**28.98**
boat	28.82	29.03	29.76	29.80	30.67	**30.74**
bridge	26.97	27.07	27.17	27.17	27.86	**27.88**
cars	29.42	29.53	29.74	29.74	30.30	**30.39**
lena	31.83	32.22	32.49	32.58	33.72	**33.85**
livingroom	26.93	27.33	27.52	27.84	**29.34**	29.19
man	29.89	30.08	30.79	30.77	31.73	**31.84**
mandrill	27.38	27.58	27.63	27.72	28.22	**28.34**
parade	26.17	26.39	27.12	27.15	27.81	**27.89**
peppers	29.83	30.46	30.27	29.96	31.46	**31.48**
skyview	26.01	26.11	27.26	27.15	28.14	**28.23**
texture	17.81	17.92	19.00	19.06	18.85	**19.08**
tree	25.61	25.80	26.42	26.42	**27.67**	27.57



Bicubic -26.01dB | SLSVR -26.11 dB | SKSVR-27.26 dB

DCNN -27.15 dB | CNN-SVM -28.14 dB | LSR-CLEAR -28.23 dB

Fig. 4. Experimental results for 'skyview' image



Bicubic – 29.83 dB | SLSVR – 30.46 dB | SKSVR – 30.27dB

DCNN – 29.96 dB | CNN-SVM – 31.46 dB | LSR-CLEAR – 31.48 dB

Fig. 5. Experimental results for 'peppers' image

It is evident from Fig.4 and Fig.5 that, the LSR-CLEAR method produces better resultant HR images in terms of quantitative measure as well as visual perception.

V. CONCLUSION AND FUTURE SCOPE

The LSR-CLEAR approach for the enhancement of low resolution images has been proposed. The LSR-CLEAR approach used deep learning for producing the learned outcomes. The application of leaky ReLU activation function helped the LSR-CLEAR approach to produce better results. The performance evaluation based on the quantitative metric PSNR indicated that the LSR-CLEAR approach outperforms the existing SR approaches. The future works will be focused on optimizing the SR methods by means of learning time and the developing image enhancement approaches for IoT based applications.

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