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New Access to Improve Super Resolution using Convolution Neural Network

Rahul Bhattacharya K. Parvathi

ABSTRACT---Super Resolution is the process to enhance image quality by increasing the pixel densities from a low resolution image. Several methods are proposed in the last few decades. We survey several methods like filtration method i.e. Scalar Smoothness Index filtration, learning based method using Convolution Neural Network. We also propose a new algorithm where we use filtration technique as a preprocessing technique of learning based method.

Keywords— Wavelet decomposition technique, SSI(Scalar Smoothness Index), SRCNN (Super-Resolution Convolution Neural Network), PSNR(Peak_Signal-to-Noise_Ratio)

I. INTRODUCTION

In the field of image processing super-resolution is an important topic which mostly reflects in the application of medical image analysis, agricultural pest detection, CCTV footage analysis for cyber investigations and satellite image enhancement.

Super Resolution (SR) is the process of improving image quality by increasing pixel densities in a Low Resolution (LR) image and obtain a High Resolution (HR) image as an output. There are many SR techniques proposed in last few decades. The popular interpolation techniques such as Bilinear, Bicubic, Lanczos, B-Spline interpolation methods can increase pixel-density but these techniques are not well enough in extraction of edge artifacts. Interpolation technique performs well in smooth region. The SSI-filtration technique is basically a high frequency image filtration technique which can extract the high frequency components i.e. the edge artifacts. The filtration technique mainly increase the contrast of the image, but for the flat region it cannot work satisfactorily. The learning based method is mainly a point-to-point mapping between LR and HR and this prior model of LR and HR image can be mapped with the help of Super-Resolution Convolution-Neural- Network (SRCNN) [16][17]. But this SRCNN method introduced a preprocessing technique only with Bicubic interpolation which draw some disadvantages of loss of artifacts and flatness.

In our paper we approach a new algorithm which can improve the SRCNN method by changing the preprocessing of Bicubic interpolation with SSI-filtration. We also study and compare the super resolution methods such as transformation technique with SSI filtration technique, SRCNN learning based method and proposed algorithm with the help of Peak-Signal-to-Noise-Ratio (PSNR).

II. RELATED WORKS

To improve the resolution or enhancing the image quality there are several methods and most importantly Image Interpolation and Super Resolution are the two methods that usually take under focus. Image Interpolation basically attempts to recover a continuous intensity function from discrete image samples based on a linear deterministic reconstruction kernel $r(\cdot)$.

$$\hat{\imath}(\varepsilon) = \sum_k c_k \, r_k(\varepsilon) \qquad (1)$$

Where c_k the interpolation coefficient is determined by input data and $r_k(\varepsilon)$ is basically a smooth function such as Spline, Sinc. There are several interpolation techniques such as Bilinear, Bicubic, B-spline, Lanczos which can increase the pixel density without adding the feature-details .But these interpolation techniques are good in case of smooth region and it could not help to distinguish the edge areas from smooth areas [1]. To overcome this problems Li [2] proposed an algorithm called Novel Edge-Directed Interpolation (NEDI) and the main idea of this NADI algorithm is to first calculate coefficients of local co-variance from a low resolution image and next employ those estimated co-variances to adapt the interpolation at higher resolution based on the geometric duality between the low-resolution co-variance and the high-resolution co-variance. Li approaches an image can be modeled as Local Gaussian Field and the local covariance matrix at each pixel is to be computed and after that the interpolation coefficient c_k can be calculated adaptively using the principal of Least Square Estimator. D. Su and P. Willis [3] introduces an algorithm is called Data Independent Triangulation which arbitrary use two triangulation to represent four-pixel square mesh. D. Su et al. [3] also used Gouraud Shading to compute pixel value at any point in triangle, which not only improve the model edges but also tends to improve proper interpolation within different geometrical meshes.

Super Resolution (SR) is the process to improve resolution or increase the pixel density in a LR image by using a pair of HR and LR images. The basic difference between Interpolation and SR method is that if a number of input image is one, the image enhancement process is known as Interpolation and if there is more than one input image, the resolution enhancement method would be called as Super Resolution [4].

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* Correspondence Author (s)
Rahul Bhattacharya, Dept. of Electronics and Telecommunication, KIIT University, Bhubaneswar, Odisha, India. (E-mail: rahul.bhattacharya10@gmail.com)
K. Parvathi, Dept. of Electronics and Telecommunication, KIIT University, Bhubaneswar, Odisha, India. (E-mail: kparvati16@gmail.com)

There are several SR methods to improve resolution and these methods are classified into five basic categories such as (i) Interpolation based, (ii) Transformation based, (iii) Reconstruction based, (iv) Filtering based and (v) Learning based. In Interpolation based most of the edge artifacts are being lost and it gets smoothed.

In Transformation Based method the LR images parameters are being transformed to another domain or different basis (like Frequency domain) using Fast Fourier Transformation (FFT) or Walsh Hadamard Transformation (WHT) or Discrete Cosine Transformation (DCT) or Wavelet Transformation [13] to extract the feature details or energy information and increase the resolution by adding the artifact details. William K. Pratt et al. [10] proposed Walsh Hadamard Transformation as a SR transformation based method for feature extraction model and also demands that it gives better performance than Fourier Transformation. P. V. Pithadia et al. [9] approaches Discrete Cosine Transformation (DCT) with Local Binary Pattern (LBP) operator for feature extraction model. Tianton Guo et al. [8] and R. Shivakumar et al. [6] proposed Wavelet Transformation for decomposing the LR images and extract frequency basis details to increase pixel density.

In Reconstruction based approach the desired HR image can be obtained from the relationship between HR and LR images and it also depends on some prior model which can assume the artifacts details of LR image and it can solve the inverse SR problem. Reconstruction based method mainly includes Maximum-a-Posteriori Probability (MAP) method, frequency domain spatial domain algorithm, iterative back-projection method etc. [11]. Minmin et al. [5] proposed a Reconstruction-based Algorithm (RBA) which is depending upon the conditioning of linear-system characterizing the model of degradation and it is analyzed in Fourier domain with the help of perturbation theory. Minmin also proposed a different approach of super resolution in which point spread function (PSF) is taken as an error bound function and it reveals that the flat or blur function can suppress the condition number (CN) of the degradation matrix and the non-integer magnification-factors (MFs) which comes from sampling zero crossing of the Discrete Fourier Transformation of PSF, gives advantage over the integer ones (1s).

Image SR reconstruction methods can be classified into two categories Multi-frame and Single-frame, Multi-frame reconstruction SR method combines the set of multiple frames of LR image of same scene for reconstruction and use iterative back projection method, projection onto convex sets (POCS) method, frequency domain method, MAP method and gives good results. But it has huge consumption of storage and computational complexity. On the other hand, Single-frame reconstruction SR method use single frame of LR image with a single input source. Image interpolation, image scaling, zooming etc. are the example of single-frame SR method. It has less storage consumption and computation complexity but it is inferior to multi-frame reconstruction SR method [12].

In filtering based method the artifact details are being extracted by using a high-pass filter, because most of the feature details are mainly stored in high frequency components. R. Sivakumar et al. [6] approached a filtering technique on a single image super resolution, where input image is first decomposed with wavelet transformation and then calculate the log energies of each decomposed band and next calculate the Scalar Sharpness Index (SSI) and filter the image with SSI parameter which gives a high resolution (HR) image. Sandeep et al. [7] introduces another filtering technique called Block-Based SSI filtering which filters the LR image blocks instead of whole LR image.

Learning based method basically based on machine learning techniques which mainly tries to capture the co-occurrence prior of LR and HR image patches and extract the feature details. Jianchao et al. [15] represent a learning based method using spare representation in terms of coupled- dictionaries jointly trained from LR and HR image-patch pairs. But the dictionary size should be optimized for better results. Detian et al. [14] proposed sparse auto-encoder (SAE) which can boost the stability and accuracy of dictionaries. Detian also introduces zero-phase component analysis (ZCA) whitening method to reduce the redundancy of the joint dictionary set. Chao et al. [16, 17] proposed a deep learning method which directly learns an end-to-end mapping between HR and LR images. The mapping is represented as Convolution-Neural-Network (CNN). Chao also shows later the sparse-code-based SR method with the help of CNN. Chaos's method optimized the hidden layers more accurately and the model they proposed called Super-Resolution Convolution Neural Network (SRCNN).

III. METHODOLOGY

1.1 Filtering based Super Resolution method

The filtration techniques can be used to improve the resolution of an image. The edge artifacts, intensity details are basically stored in the high-frequency components and the low-frequency components store the texture details. So the filtration technique is employed for filtering out the ill-posed edge artifacts and intensity details from the LR image. In this paper we are going to discuss about filtration based SR method with SSI parameter. Firstly a three-level Discrete Wavelet Transformation (DWT) is performed to decompose the LR image and compute the sub-bands of the image namely LL, LH, HL, HH.

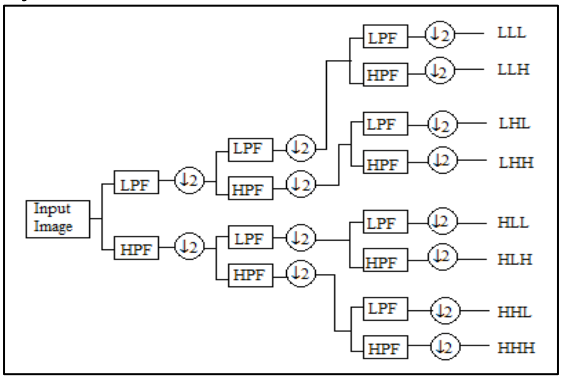

Fig. 1. 3-level DWT decomposition

In the next step the log energies of every sub-bands are to be calculated as, [20]

$$E_{XY_k} = \log_{10}(1 + \frac{1}{N_k}\sum_{i,j} S^2{}_{XY_k}(i,j)) \quad (2.1)$$

Where, XY = {LH, HL, HH}, $N_k, k \in \{1,2,3\}$ is the number of coefficient in sub-bands at level k, and S_{XY_k} is the subband levels of DWT. Now the weighted log energy for each decomposition level can be calculated as, [6]

$$E = (1-w) * \left(\frac{E_{LH} + E_{HL}}{2}\right) + w * E_{HH} \quad (2.2)$$

Where w : Weightage value And lastly the Scalar Sharpness Index parameter are to be calculated as, [6]

$$SSI = \sum_{n=1}^{3} 2^{L-n} E_n \quad (2.3)$$

In above equation 2.5, 'L' is the factor which is greater than or equal to n. Finally we filter out the high frequency edge artifacts with a multidimensional filter using SSI as a scalar filter parameter which gives a high resolution enlarge output image with high contrast.

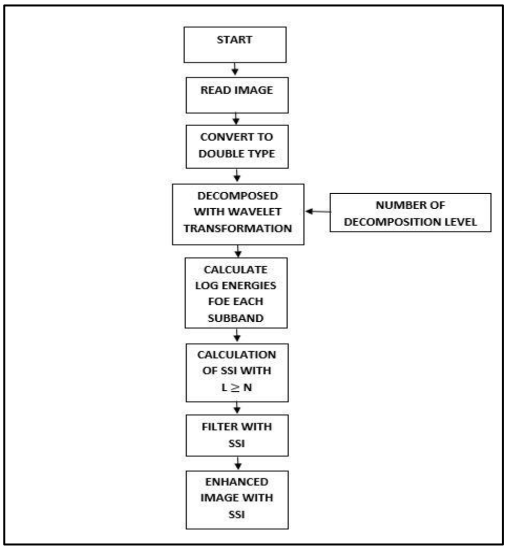

Fig. 2. Flowchart of SSI filtration for SR method

1.2. Learning based Super Resolution method

This SR method is a prior model mapping between LR and HR image and this mapping can be done by using any type of neural network such as Feedforward-Neural-Network, Recurrent-Neural-Network (RNN), Modular-Neural-Network (MNN), Kohonen-Self-Organizing-Neural-Network and Convolution-Neural-Network (CNN). In our paper we are going to discuss about the CNN based learning method for super resolution i.e. SRCNN [16] [17]. This process can be done in three basic steps i.e. (I) Patch extraction, (II) Non-linear mapping, (III) Reconstruction.

(I) Path extraction: In this step we first extract the overlapping patches from the LR image X and next these patches are represented as high-dimensional vectors which comprise of a set of artifact maps. The number of sets of artifact maps indicates the dimensionality of the vectors. The overlapping patches can be extracted by convolving the LR image with a set of trained filters with a basis. This filters basically implement a set of networks. First layer is formally expressed as an operational function F_1, [16]

$$F_1(X) = \max(0, S_1 * X + A_1) \quad (3.1)$$

Where [21], B_1 and W_1 represents the basis and the filters respectively and '$*$' represents the convolution operator. 'S_1' represents n_1 filters of size $c \times g_1 \times g_1$, where g_1 is the size of a filter and c denotes the number of channels lies in input image. 'S_1' performs n_1 times of convolutions on the LR image and each convolution step holds a karnel size $c \times g_1 \times g_1$. The output is comprised of artifact maps and A_1 is an n_1- dimensional vector. A filter is connected with each element of n_1- dimensional vector. Rectified-Linear-Unit (ReLU) [18] is applied on the filter response.

(II) Non-linear mapping: In that operation the high-dimensional vector maps onto another high-dimensional vector. These mapped-vectors are basically the high-dimensional patch which comprise another set of artifact maps. Here we basically map each n_1-dimensional vectors onto n_2- dimensional vectors. In this case the patches are the convolved filter extracted patch of the artifact map. Second layer operation can be expressed as F_2, [16]

$$F_2(X) = \max(0, S_2 * X + A_2) \quad (3.2)$$

Here [21], S_2 consist of n_2 filters of size $n_2 \times g_2 \times g_2$, and A_2 is a n_2- dimensional-basis. Each output is a n_2-dimensional-vector which represents high-resolution-patch that will be employed for reconstruction. To increase the nonlinearity it is possible to add more convolution layer.

(III) Reconstruction: The above high-resolution patches are aggregated in this operations to produce the final high-resolution image. It is expected that this image must be matched with the ground truth Y. Mostly the resultant high resolution images are generated by averaging the predicted overlapping high-resolution patches. A set of pre-defined filters on a feature map is considered as a tool for averaging where each position of the 'flattened' vector is basically represents a high-resolution-patch. Third convolution layer can be formulated as, [16]

$$F_3(X) = S_3 * F_2(X) + A_3 \quad (3.3)$$

Where, S_3 represents c number of filters supports $n_2 \times g_3 \times g_3$ and A_3 is a c-dimensional-basis-vector.

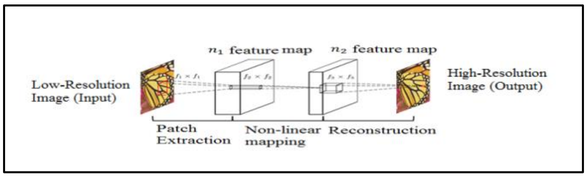

Fig. 3. Methodical diagram of learning based SR method (SRCNN) with 3 layers

1.3 Proposed algorithm for Super Resolution method

The proposed algorithm is basically generated to improve the SRCNN methodology. In SRCNN technique the low resolution image is initially interpolated by bicubic interpolation method for enlargement which is named as a preprocessing technique of learning based SR method.

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Now as we know that the interpolation technique smoothen the low resolution image artifacts, so if the filtration technique is used as a preprocessing technique instead of only using interpolation technique, the output will give a high resolution image with better artifact details.

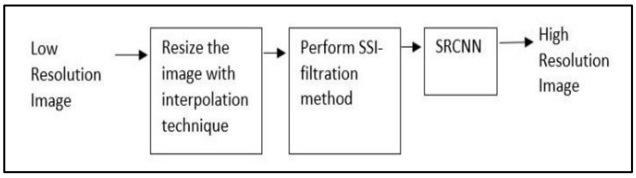

Fig. 4. Processing step block diagram of proposed algorithm

IV. RESULTS AND DISCUSSION

In this paper we use MATLAB, 2017 software to execute our methodologies. In case of our study we consider two parameters Peak-Signal-to-Noise-Ratio (PSNR) to compare the qualitative improvement of LR image after super resolution.

In SSI filtration technique we will be taking the weightage (w) and 'L' parameter accordingly, which is the best suited value for a specific LR image. In case of SRCNN methodology we have taken a filter setup specification as g_1= 9, g_2= 5, g_3= 5, n_1= 64, n_2= 32 and convolution biases as a_1= 64×1, a_2= 32×1, a_3= 1×1. [16][17]

In our paper we choose nine different types of pictures and execute the above mentioned methodologies for super resolution in order to get a HR enlarged output image. We perform the methodologies in different image patches with an upscaling factor of four (4) for enlargement.

Fig. 5. Input Low Resolution Image set

Now for different SR methodologies the nine picture patches are giving results as,

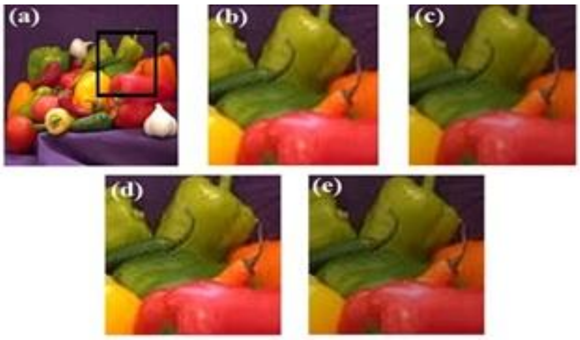

Fig. 5.1. (a) Original image with patch size 79x70 pixels, (b) Interpolated image, (c) SSI filtered image (W=0.8 and L=7), (d) SRCNN output image, (e) Proposed algorithm output image.

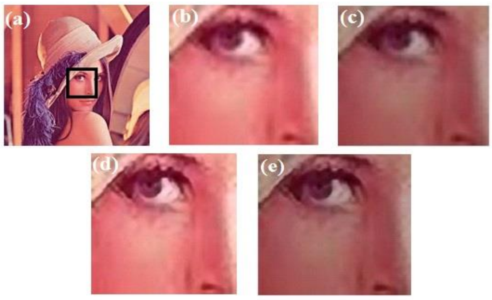

Fig. 5.2. (a) Original image with patch size 38x38 pixels, (b) Interpolated image, (c) SSI filtered image (W=0.8 and L=6), (d) SRCNN output image, (e) Proposed algorithm output image.

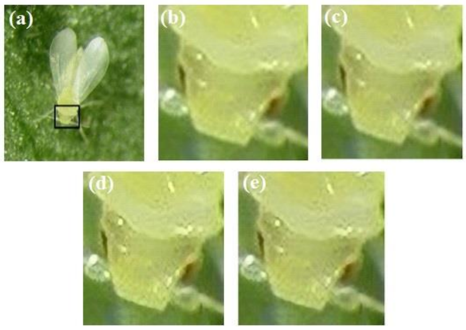

Fig. 5.3. (a) Original image with patch size 75x56 pixels, (b) Interpolated image, (c) SSI filtered image (W=0.8 and L=8), (d) SRCNN output image, (e) Proposed algorithm output image.

Fig. 5.4. (a) Original image with patch size 114x131 pixels, (b) Interpolated image, (c) SSI filtered image (W=0.9 and L=3), (d) SRCNN output image, (e) Proposed algorithm output image

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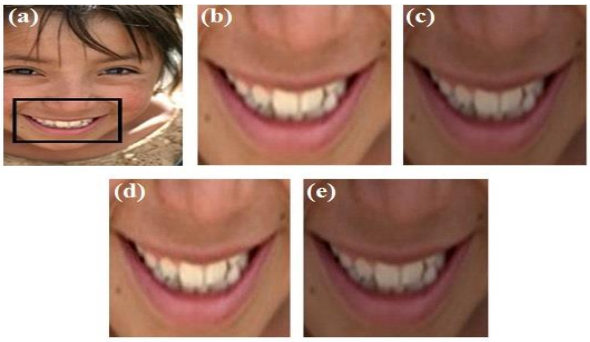

Fig. 5.5. (a) Original image with patch size 131x83 pixels, (b) Interpolated image, (c) SSI filtered image (W=0.8 and L=10), (d) SRCNN output image, (e) Proposed algorithm output image.

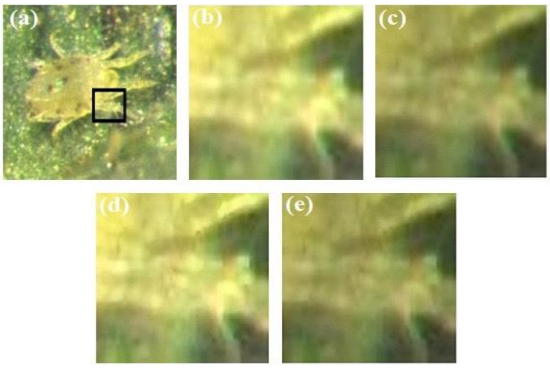

Fig. 5.6. (a) Original image with patch size 52x36 pixels, (b) Interpolated image, (c) SSI filtered image (W=0.8 and L=9), (d) SRCNN output image, (e) Proposed algorithm output image.

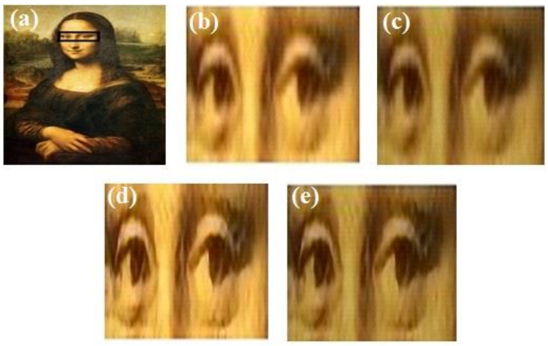

Fig 5.7. (a) Original image with patch size 67x16 pixels, (b) Interpolated image, (c) SSI filtered image (W=0.9 and L=7), (d) SRCNN output image, (e) Proposed algorithm output image.

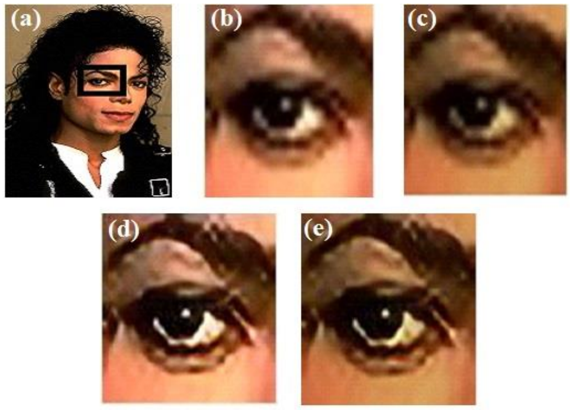

Fig. 5.8. (a) Original image with patch size 27x20 pixels, (b) Interpolated image, (c) SSI filtered image (W=0.8 and L=5), (d) SRCNN output image, (e) Proposed algorithm output image.

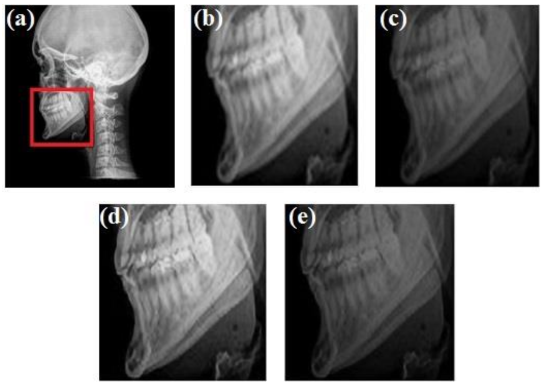

Fig. 5.9. (a) Original image with patch size 81x67 pixels, (b) Interpolated image, (c) SSI filtered image (W=0.8 and L=6), (d) SRCNN output image, (e) Proposed algorithm output image.

Table 1. PSNR Comparison Table

IMAGES	SSI-FILTRATION	SRCNN	PROPOSED ALGO.
Fruit (79X70)	70.2031	89.3158	91.6950
Lena (38X38)	65.2271	83.1984	86.5110
White Fly (75X56)	84.2889	89.1451	89.5944
Fly Body (114X131)	61.1170	72.8811	77.8345
Child (131X83)	64.3273	101.0842	105.3360
Leaf Insect (52X36)	64.7019	92.7475	97.3267
Monalisa (67X16)	67.2601	81.4415	84.1341
Michael (27X20)	70.4698	73.0793	74.8079
Human Skull (81X67)	62.6069	85.4084	91.7156

The above results shows that the original small image patches are enlarged with a scaling factor 4 and the outputs are the high-resolution image patches. The results of proposed methods are little dark in compare to others because some of the averaged or predicted pixel values of enlarged image is replaced by 255 after filtration. The comparison table of PSNR basically computed with respect to the enlarged interpolated image for SSI-Filtration and SRCNN methods. And for our proposed algorithm we calculate the PSNR w.r.t the preprocessing output value i.e. the output value of SSI filtration.

V. CONCLUSION

Our paper presents a thorough overview of super resolution methodologies which has been proposed for several years. We also approach a new algorithm to enhance the usefulness of Super-resolution Convolution Neural Network (SRCNN) technique. The proposed algorithm shows a better result in compare to SRCNN with interpolation as a preprocessing technique. It is also noticeable that with a proper SSI filtration parameter value a low resolution image can be enhanced with better artifact and intensity details. For image 4 we got the best PSNR value of 105.33.

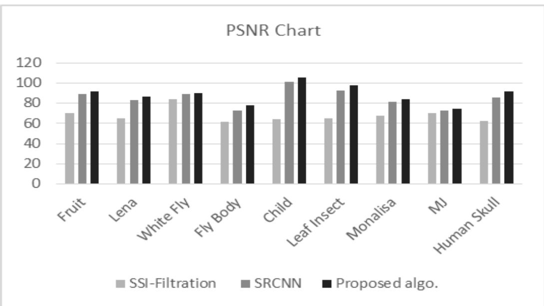

Fig. 6. PSNR Chart of nine images

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