ISSN2394-3777 (Print)
ISSN2394-3785 (Online)
Available online atwww.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 12, April 2018

Sparsity Based Single Image Super Resolution of Colour Images

Helena Thomas [1], Anitha R [2]

P.G. Student, Department of Computer Engineering, College of Engineering kidangoor, kottayam, Kerala, India[1]helenathomas2007@gmail.com[1]

Assistant Professor, Department of Computer Engineering, College of Engineering kidangoor, kottayam, Kerala, India[2]

anitharshibu@gmail.com[2]

***Abstract*— There are a wide variety of methods for improving the resolution of images. However, the most existing methods focus on super resoluting along the colour channels by considering luminance channel information also into account. The existing methods are tedious, time consuming and with lot of processing overhead. The present method achieves sparsity based super resolution by considering super resolution along the luminance channel. The present method works in less time and exhibits better performance. A dictionary learning method that encourage edge similarities is also used. Super Resolution task encounters an issue that much information is lost in the process of going from high resolution images to low resolution images and hence the solution is not unique. The present method effectively handles this issue. The advantages of this method are demonstrated both visually and quantitatively using image quality metrics.**

Key words: Colour Super Resolution, Single-image super Resolution, Sparse Coding, Dictionary Learning, Edge Similarity

I. Introduction

Super Resolution (SR) of an image is the process of obtaining a high-resolution image by enhancing a low-resolution input image. 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, the more image details. The resolution of a digital image can be classified in many different ways: pixel resolution, spatial resolution, spectral resolution, temporal resolution, and radiometric resolution.

Super-resolution (SR) are techniques that construct high-resolution (HR) images from several observed low-resolution (LR) images, thereby increasing the high frequency components and removing the degradations caused by the imaging process of the low-resolution camera. The basic idea behind SR is to combine the non-redundant information contained in multiple low-resolution frames to generate a high-resolution image. A closely related technique with SR is the single image interpolation approach, which can be also used to increase the image size. However, since there is no additional information provided, the quality of the single image interpolation is very much limited due to the ill-posed nature of the problem, and the lost frequency components cannot be recovered. In the SR setting, however, multiple low-resolution observations are available for reconstruction, making the problem better constrained. The non-redundant information contained in the these LR images is typically introduced by subpixel shifts between them. These subpixel shifts may occur due to uncontrolled motions between the imaging system and scene, e.g., movements of objects, or due to controlled motions, e.g., the satellite imaging system orbits the earth with predefined speed and path.

The Super Resolution task encounters an issue that much information is lost in the process of going from high resolution images to low resolution images and hence the solution is not unique. Consequently, strong prior information is incorporated to yield realistic and robust solutions. Example priors include knowledge of the underlying scene, distribution of pixels, historical data, smoothness and edge information and so on.

In contrast to conventional super resolution problem with multiple low-resolution images as input, single image super resolution methods have been developed recently that generate the high-

ISSN2394-3777 (Print)
ISSN2394-3785 (Online)
Available online atwww.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 12, April 2018

resolution image only based on a single low-resolution image. Classically, the solution to this problem is based on example-based methods exploiting nearest neighbour estimations, where pairs of low and high-resolution image patches are collected, and each low-resolution patch is mapped to a corresponding high-resolution patch.

II. LITERATURE SURVEY

A. "Screen Content Image Segmentation Using Sparse Decomposition and Total Variation Minimization" S. Minaee and Y. Wang [1]

Sparse decomposition has been widely used for different applications, such as source separation, image classification, image denoising and more. The paper presents a new algorithm for segmentation of an image into background and foreground text and graphics using sparse decomposition and total variation minimization. The proposed method is designed based on the assumption that the background part of the image is smoothly varying and can be represented by a linear combination of a few smoothly varying basis functions, while the foreground text and graphics can be modelled with a sparse component over laid on the smooth background.

The background and foreground are separated using a sparse decomposition framework regularized with a few suitable regularization terms which promote the sparsity and connectivity of foreground pixels. This algorithm has been tested on a dataset of images extracted from HEVC standard test sequences for screen content coding and is shown to have superior performance over some prior methods.

B. "Soft Edge Smoothness Prior to Alpha Channel Super Resolution" S. Dai, M. Han, W. Xu, Y. Wu, and Y. Gong [2],

Effective image prior is necessary for image super resolution, due to its severely under-determined nature. Although the edge smoothness prior can be effective, it is generally difficult to have analytical forms to evaluate the edge smoothness, especially for soft edges that exhibit gradual intensity transitions. This paper finds the connection between the soft edge smoothness and a soft cut metric on an image grid by generalizing the Geocuts method and proves that the soft edge smoothness measure approximates the average length of all level lines in an intensity image. The new finding not only leads to an analytical characterization of the soft edge smoothness prior but also gives an intuitive geometric explanation. Regularizing the super resolution problem by this new form of prior can simultaneously minimize the length of all level lines, and thus resulting in visually appealing results.

C. "Super-Resolution Image Reconstruction" S. C. Park, M. K. Park, and M. G. Kang [3],

SR image reconstruction is proved to be useful in many practical cases where multiple frames of the same scene can be obtained, including medical imaging, satellite imaging, and video applications. The basic premise for increasing the spatial resolution in SR techniques is the availability of multiple LR images captured from the same scene. Registration is a very important step to the success of the SR image reconstruction.SR image reconstruction is one of the most spotlighted research areas because it can overcome the inherent resolution limitation of the imaging system and improve the performance of most digital image processing applications. Robustness and flexibility in modelling noise characteristics and a priori knowledge about the solution are the major advantages of the stochastic SR approach.

The SR technique is also useful in medical imaging such as computed tomography (CT) and magnetic resonance imaging (MRI) since the acquisition of multiple images is possible while the resolution quality is limited. In satellite imaging applications such as remote sensing and LANDSAT, several images of the same area are usually provided, and the SR technique to improve the resolution of the target can be considered. Another application is a conversion from an NTSC video signal to an HDTV signal since there is a clear and present need to display an SDTV signal on the HDTV without visual artifacts.

D. "Image Up sampling via Imposed Edge Statistics" Raanan Fattal [4],

A new method for up sampling images which can generate sharp edges with reduced input resolution grid-related artifacts. The method is based on a statistical edge dependency relating certain edge features of two different resolutions, which is generically exhibited by real-world images. While other solutions assume some form of smoothness, we rely on this distinctive edge dependency as our prior knowledge in order to increase image resolution.

In addition to this relation, we require that intensities are conserved; the output image must be identical to the input image when down sampled to the original resolution. Altogether the method

ISSN2394-3777 (Print)
ISSN2394-3785 (Online)
Available online atwww.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 12, April 2018

consists of solving a constrained optimization problem, attempting to impose the correct edge relation and conserve local intensities with respect to the low-resolution input image. Results demonstrate the visual importance of having such edge features properly matched, and the capability of the method to produce images in which sharp edges are successfully reconstructed.

E. "Single Image Super-Resolution" D. Glasner, S. Bagon, and M. Irani [5],

In the first approach, HR patches are constructed using a sparse representation of the corresponding LR patch in a compact dictionary. In the second approach, exploit the repetition of local visual content within and across different scales of the given LR image. Image super-resolution is the task of obtaining a high-resolution (HR) image of a scene given low-resolution (LR) image(s) of the scene. High resolution means high pixel density, also referred to as high-definition (HD). A HR image brings out details that would be blocked out in a LR image. More pixels in the same area implies a higher sampling frequency thereby offering more details. Bicubic interpolation is frequently used to increase the number of pixels in an image. However, it cannot recover original high frequency details of the scene if the scene is not sampled at a rate higher than the Nyquist frequency.

F. "Joint dictionary learning for example-based image super-resolution" Mojtaba Sahraee-Ardakan, Mohsen Joneidi [6],

A new joint dictionary learning method for example-based image super resolution (SR), using sparse representation. The low-resolution (LR) dictionary is trained from a set of LR sample image patches. Using the sparse representation coefficients of these LR patches over the LR dictionary, the high-resolution (HR) dictionary is trained by minimizing their construction error of HR sample patches. The error criterion used here is the mean square error. In this way, the HR patches have the same sparse representation over HR dictionary as the LR patches over the LR dictionary, and at the same time, these sparse representations can well reconstruct the HR patches.

III. PROPOSED METHOD

The aim of the project is given a single low-resolution input, reconstruct a high-resolution version of the input. Resulting image should represent reality better than the input image.
The entire project is divided into two steps:

1) Dictionary Creation.
2) Super Resolution

1) *Dictionary Creation:* Construct two coupled dictionaries based on image patches in luminance (Y) channel, which is a low-resolution dictionary (Dl) consisting of high frequency features and a high-resolution dictionary (Dh) consisting of actual high-resolution patches. Atoms of each dictionary correspond to each other and are LR-HR counterparts of each other extracted from the same locations.

Initialize the parameters, where the dictionary size is 1024 atoms, the sparsity regularization parameter lambda is 0.15, patch size is 5, upscaling factor is 2 and 1,00,000 image patches are set as training set.

Generation of high-resolution and low-resolution image patches are as follows:

1) Initialize high resolution and low-resolution image patches as Xh and Xl.
2) Divide the input image into patches and these patches are taken as high-resolution counterparts of the input image.
3) Generate low resolution counter parts of the input image using bicubic interpolation.
4) Compute the first order and second order gradient features which is Xh and Xl.
5) Xh and Xl patches are pruned or trimmed i.e., those patches whose feature's variance is above a specified threshold (10) is only taken. So, we get a reduced Xh and Xl image patches.

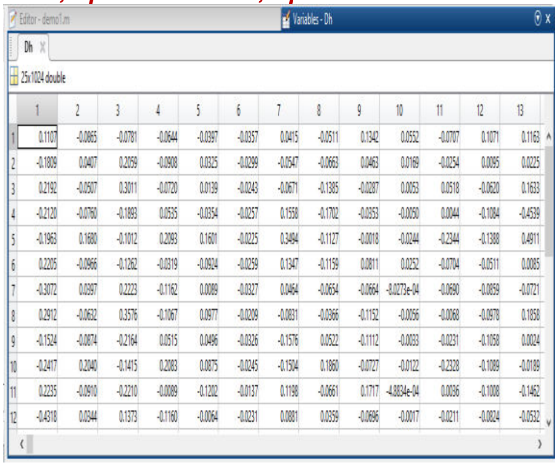
Generation of high-resolution and low-resolution dictionary are as follows:

1) Normalization of Xh and Xl image patches.
2) For joint learning of dictionary combine Xh and Xl to get X.
3) Normalize X.

Create dictionary using Regularised Sparse Coding method which is the proposed method by solving optimization problem.Optimization problem is the problem of finding the best solution from all feasible solutions. Repeat until the desired number of iterations are completed. Now, we obtain the high-resolution dictionary (Dh) and low-resolution dictionary (Dl).

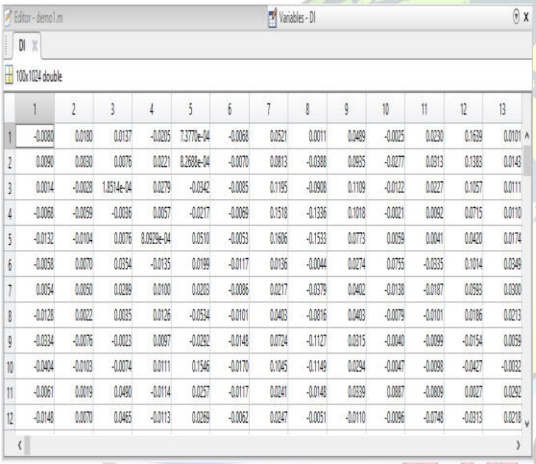
ISSN2394-3777 (Print)
ISSN2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 12, April 2018



	1	2	3	4	5	6	7	8	9	10	11	12	13
1	0.1107	-0.0865	-0.0781	-0.0644	-0.0397	-0.0357	0.0415	-0.0511	0.1342	0.0552	-0.0707	0.1071	0.1163
2	-0.1809	0.0407	0.2059	-0.0908	0.0325	-0.0299	-0.0547	-0.0663	0.0463	0.0169	-0.0254	0.0095	0.0225
3	0.2192	-0.0507	0.3011	-0.0720	0.0139	-0.0243	-0.0671	-0.1385	-0.0287	0.0053	0.0518	-0.0620	0.1633
4	-0.2120	-0.0760	-0.1893	0.0535	-0.0354	-0.0257	0.1558	-0.1702	-0.0353	-0.0050	0.0044	-0.1084	-0.4539
5	-0.1963	0.1680	-0.1012	0.2093	0.1601	-0.0225	0.3494	-0.1127	-0.0018	-0.0244	-0.2344	-0.1388	0.4911
6	0.2205	-0.0966	-0.1262	-0.0319	-0.0924	-0.0259	0.1347	-0.1159	0.0811	0.0252	-0.0704	-0.0511	0.0085
7	-0.3072	0.0397	0.2223	-0.1162	0.0089	-0.0327	0.0464	-0.0654	-0.0664	-8.0273e-04	-0.0690	-0.0859	-0.0721
8	0.2912	-0.0632	0.3576	-0.1067	0.0977	-0.0209	-0.0831	-0.0366	-0.1152	-0.0056	-0.0068	-0.0978	0.1858
9	-0.1524	-0.0874	-0.2164	0.0515	0.0496	-0.0326	-0.1576	0.0522	-0.1112	-0.0033	-0.0231	-0.1058	0.0024
10	-0.2417	0.2040	-0.1415	0.2083	0.0875	-0.0245	-0.1504	0.1860	-0.0727	-0.0122	-0.2328	-0.1089	-0.0189
11	0.2235	-0.0910	-0.2210	-0.0089	-0.1202	-0.0137	0.1198	-0.0661	0.1717	-4.8834e-04	0.0036	-0.1008	-0.1462
12	-0.4318	0.0344	0.1373	-0.1160	-0.0064	-0.0231	0.0881	0.0359	-0.0696	-0.0017	-0.0211	-0.0824	-0.0532

Fig. I High Resolution Dictionary, Dh



	1	2	3	4	5	6	7	8	9	10	11	12	13
1	-0.0080	0.0180	0.0137	-0.0205	7.3770e-04	-0.0068	0.0521	0.0011	0.0489	-0.0025	0.0230	0.1639	0.0101
2	0.0090	0.0030	0.0076	0.0221	8.2688e-04	-0.0070	0.0813	-0.0388	0.0935	-0.0277	0.0313	0.1383	0.0143
3	0.0014	-0.0028	1.8514e-04	0.0279	-0.0342	-0.0085	0.1195	-0.0908	0.1109	-0.0122	0.0227	0.1057	0.0111
4	-0.0068	-0.0059	-0.0036	0.0057	-0.0217	-0.0069	0.1518	-0.1336	0.1018	-0.0021	0.0092	0.0715	0.0110
5	-0.0132	-0.0104	0.0076	8.0929e-04	0.0510	-0.0053	0.1606	-0.1533	0.0773	0.0059	0.0041	0.0420	0.0174
6	-0.0058	0.0070	0.0354	-0.0135	0.0199	-0.0117	0.0136	-0.0044	0.0274	0.0755	-0.0335	0.1014	0.0349
7	0.0054	0.0050	0.0289	0.0100	0.0203	-0.0086	0.0217	-0.0379	0.0402	-0.0138	-0.0187	0.0593	0.0300
8	-0.0128	0.0022	0.0035	0.0126	-0.0534	-0.0101	0.0403	-0.0816	0.0403	-0.0079	-0.0101	0.0186	0.0213
9	-0.0334	-0.0076	-0.0023	0.0097	-0.0292	-0.0148	0.0724	-0.1127	0.0315	-0.0040	-0.0099	-0.0154	0.0059
10	-0.0404	-0.0103	-0.0074	0.0111	0.1546	-0.0170	0.1045	-0.1149	0.0294	-0.0047	-0.0098	-0.0427	-0.0032
11	-0.0061	0.0019	0.0490	-0.0114	0.0257	-0.0117	0.0241	-0.0148	0.0339	0.0887	-0.0809	0.0027	0.0292
12	-0.0148	0.0070	0.0465	-0.0113	0.0269	-0.0062	0.0247	-0.0051	-0.0110	-0.0096	-0.0748	-0.0313	0.0218

Fig. IILow Resolution Dictionary, Dl

2) Super Resolution: Super Resolution of a low-resolution input image is done as follows:

1) Normalize the dictionary.
2) Initialize an image array, HR image X = 0.
3) Construct or upscale the low-resolution image using bicubic interpolation method.
4) Extract low-resolution image features by computing the first-order and second-order gradient (edge) features of the upscaled image.
5) Avoid boundary of patches to reduce error in Sparse Recovery.
6) Loop to recover each low-resolution patch.
    a. Sparse recovery using L1QP_FeatureSign_yang by solving nonnegative quadratic programming using Feature Sign

$$z = \arg\min_{\alpha} \frac{1}{2}\| D_l\, \alpha - y\|_2^2 + \lambda\|\alpha\|_1$$

    b. Recover HR patch feature

$$x = D_h z / \| D_h z \|_2$$

    c. Recover HR image patch

$$x_p = (c \times r) \cdot x + m$$

$$m = \text{mean}(y_p),\ r = \|y_p - m\|_2;$$

7) Add corresponding super-resoluted image patch to X
8) Fill in the empty spaces in the output image patch with bicubic interpolation
9) The final output image obtained is the HR image X.

Colour Super Resolution: The colour super resolution is performed in YCbCr space: Apply Bicubic interpolation on Cb and Cr channels. Human eye is more sensitive to luminance than chrominance. Some images have varying amount of luminance and chrominance geometry. Chrominance channels also contain useful information. Super-resolution only on luminance channel may not get the best results. Luminance edge (in Y) is presented in R, G and B channels.

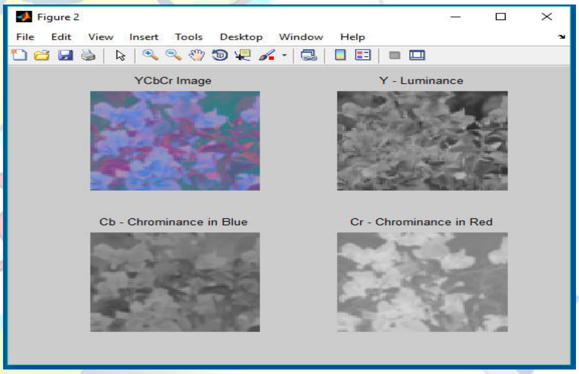


Fig. III YCbCr channel extraction of the output image

Capturing of Edge Similarities: Extract edge information in RGB channels find patches that should have high edge correlation based on amount of colour information in each patch Encourage edge similarity in selected patches of high resolution image Similarity (Correlation) between edges in different channels. (Based on HR image) Colour constraints: Edge differences across colour channels are minimized for selected patches.

EXPERIMENTAL RESULTS

ISSN2394-3777 (Print)
ISSN2394-3785 (Online)
Available online atwww.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 12, April 2018

We have super resoluted the low-resolution input image into a high-resolution image. The obtained high-resolution image is an enhanced version of the input image.

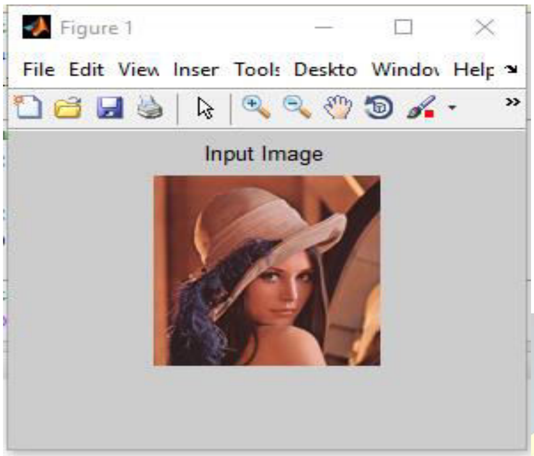


Fig. IVLow Resolution Input image

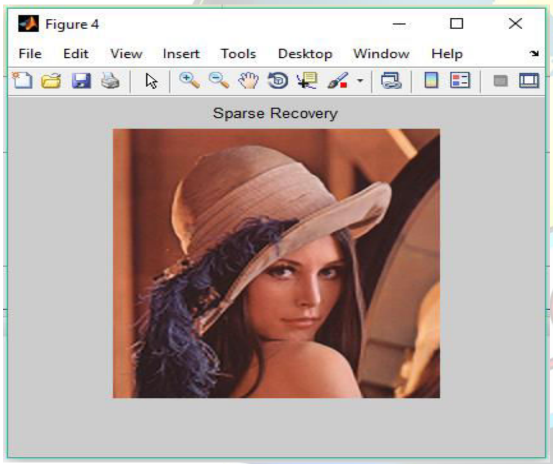


Fig. VHigh Resolution Output image

Performance Evaluation: Quantitative measures used for performance evaluation are Peak Signal to Noise Ratio (PSNR), Root Mean Square Error measure (RMSE) and time of computation.

1) Peak Signal to Noise Ratio (PSNR):

Peak signal-to-noise ratio, often abbreviated as PSNR, is a term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

PSNR is most commonly used to measure the quality of reconstruction of lossy compression codecs (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codecs, PSNR is an approximation to human perception of reconstruction quality.

Typical values for the PSNR in lossy image and video compression are between 30 and 50 dB, provided the bit depth is 8 bits, where higher is better. For 16-bit data typical values for the PSNR are between 60 and 80 dB. Acceptable values for wireless transmission quality loss are considered to be about 20 dB to 25 dB. In the absence of noise, the two images I and K are identical, and thus the MSE is zero. In this case the PSNR is infinite.

The PSNR (in dB) is defined as:

$$\begin{aligned} PSNR &= 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\ &= 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \\ &= 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE) \end{aligned}$$

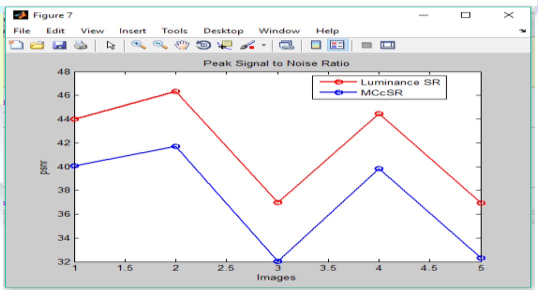


Fig.VIGraph showing variation of PSNR values.

2) Root Mean Square Error measure (RMSE):

The root-mean-square deviation (RMSD) or root-mean-square error (RMSE) (or sometimes root-mean-squared error) is a frequently used measure of the differences between values (sample and population values) predicted by a model or an estimator and the values actually observed. The RMSD represents the sample standard deviation of the differences between predicted values and observed values. These individual differences are called residuals when the calculations are performed over the data sample that was used for estimation, and are called prediction errors when computed out-of-sample. RMSD is a measure of accuracy, to compare forecasting errors of different models for a particular data and not between datasets, as it is scale-dependent.

The RMSD of an estimator θ with respect to an estimated parameter $\theta^{\wedge}$ is defined as the square root of the mean square error :

$$\mathrm{RMSD}(\hat{\theta}) = \sqrt{\mathrm{MSE}(\hat{\theta})} = \sqrt{\mathrm{E}((\hat{\theta} - \theta)^2)}.$$

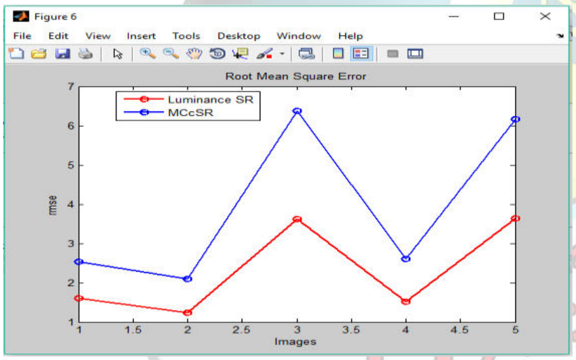


Fig.VII Graph showing variation of RMSE values.

3) Time of computation:

Time complexity is simply a measure of the time it takes for a function or expression to complete its task, as well as the name of the process to measure that time. It can be applied to almost any algorithm or function but is more useful for recursive functions. Time complexity is expressed typically in the "big O notation," but there are other notations. This is a mathematical representation of the upper limit of the scaling factor for an algorithm and is written as O(Nn), with "N" being the number of inputs and "n" being the number of looping expressions.

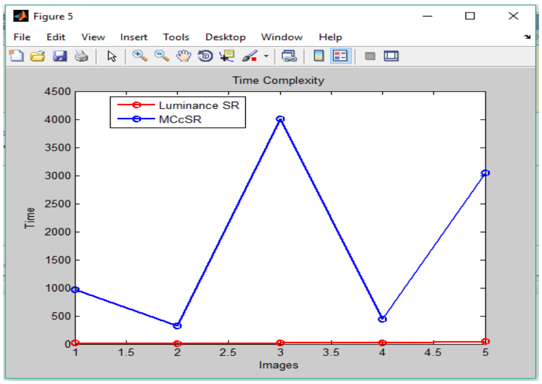


Fig.VIII Graph showing variation of Computational Time.

Table 1 Computational time, PSNR and RMSE values for the proposed method (Sparse Coding)

Image	Computational Time	RMSE	PSNR
1	15.2044	1.6089	44.00007
2	12.0906	1.2281	46.3461
3	13.5425	3.6156	36.9671
4	13.2298	1.5228	44.4778
5	43.8600	3.6328	36.9257

Table 2 Computational time, PSNR and RMSE values for the existing method (MCcSR)

Image	Computational Time	RMSE	PSNR
1	962.8967	2.5293	40.0706
2	326.1475	2.0935	41.7131
3	4.0037e+03	6.3843	32.0284
4	437.0939	2.6029	39.8213
5	3.0513e+03	6.1706	32.3241

From the Tables 1 and 2, it is observed that the proposed method (Sparse Coding) has higher Peak Signal to Noise Ratio and lower values of Root Mean Square Error and Computational time compared to the existing method (MCcSR). So, the Proposed method exhibits better Performance than the existing method.

ISSN2394-3777 (Print)
ISSN2394-3785 (Online)
Available online atwww.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 5, Special Issue 12, April 2018

IV. Conclusion

In this system, I had developed a system that super resolute a single image based on sparsity. The system is initialized by setting dictionary size as 1024 atoms, training set of images as 1,00,000, patch size as 5x and scaling factor as 2. The quantitative measures used for performance evaluation are Peak Signal to Noise Ratio (PSNR), Root Mean Square Error (RMSE) and time of computation. From experimental results it is observed that the proposed method has higher PSNR values and lower RMSE and Computational values when compared with the existing method. Thus, the proposed method exhibits better performance than the existing method.

The proposed methodology can be further tested with different patch sizes, upscaling factors and under different dictionary sizes, different noise levels and the performance variation can be plotted and evaluated. Also, introduce other objective measurements rather than MSE for quality assessment. Apply other cross channel constraints that can further improve super resolution performance.

References

[1] S. Minaee and Y.Wang, “Screen Content Image Segmentation Using Sparse Decomposition and Total Variation Minimization” in Proc. IEEE. Conf. on Image Processing, 2015, pp. 3295-3299.

[2] S. Dai, M. Han, W. Xu, Y. Wu, and Y. Gong, “Soft Edge Smoothness Prior to Alpha Channel Super Resolution,”in Proc. IEEE Conf. Computer Vision Pattern Recognition, 2007, pp.1-8.

[3] S. C. Park, M. K. Park, and M. G. Kang, “Super-Resolution Image Reconstruction” in Signal Processing Magazine, IEEE, vol. 20, no. 3, pp. 21-36, 2003.

[4] Raanan Fattal, “Image Up sampling via Imposed Edge Statistics” in ACM Trans. Graph. (TOG), vol. 26, no. 95.

[5] D. Glasner, S. Bagon, and M. Irani, “Single Image Super-Resolution” in Proc. IEEE Conf. on Computer Vision, 2009, pp. 349-356.

[6] Mojtaba Sahraee-Ardakan, Mohsen Joneidi, “Joint dictionary learning for example-based image super-resolution” in Computer Vision and Pattern Recognition, 2017.

