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MULTISPECTRAL SUPER RESOLUTION AND IMAGE QUALITY ASSESSMENT COMPARATIVE ANALYSIS

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Abstract—The satellite image resolution alludes to highest accuracy to capture finer details from scene. This paper addresses five different techniques to improve resolution of multispectral satellite image. Our algorithm generates super resolved multispectral image using advantages of Patch Based processing. The results are then compared with four techniques Bicubic Interpolation, Edge Directed Orientation, Patch Based Processing, Gaussian Process Regression (GPR). Comparative analysis is carried out with reference to Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Image Fidelity, correlation coefficient and similarity measure, processing speed and storage space required. Image quality assessments (IQA) parameters are also performed. Super resolution (SR) is commercial algorithm to improve resolution of satellite image when we compare with image fusion.

Keywords—Image Quality, Super Resolution, Image Fusion, Multispectral Image, Candidate Pixel

I. INTRODUCTION

A. Image Resolution

Image resolution is a quantity, how best the information can be represented on 2 dimensional planes (2D-plane). When we deal with resolution of an image it is refers to the spatial and temporal resolution. Spatial resolution signifies the number of pixels along rows and columns, video is sequence of frames (images) over a period of time, temporal resolution signify the number of frames per second (fps), for a best quality always more number of frames are preferred. In most of the image or video processing application the spatial and temporal resolutions do have its significance. When we deal with satellite imaging priority is given to temporal resolution. As high temporal resolution identification and classification is more accurately possible.

B. Image Super Resolution Reconstruction

A digital imaging application requires high-resolution image/video for further image processing and analysis. The high-resolution images are mainly required for accurate information for human interpretation and automatic machine perception. Image resolution describe the niceties contained in the image, as higher the resolution more the details. Image resolution can be represented in different ways: pixel resolution, spatial resolution, temporal resolution, spectral resolution and radiometric resolution. Always types of resolution require always goes with kind of applications and it need not be the same for all. Digital image is made up of small picture elements called pel/pixel. In satellite images spatial resolution is vital, for accurate analysis and sympathetic. Spatial resolution refers to pixel density in an image and it's represented as pixels per inch (PPI). Spatial resolution depend on- imaging sensors/ the image acquisition device, present image sensors are typically Charge Coupled Device (CCD) / Complementary Metal Oxide Semiconductor (CMOS), these sensors are two dimensional (2D) array to capture 2D signal. Increasing sensor density and decreasing dimension of sensor which is expensive i.e. hardware cost increases but as the size of the sensors reduced the shot noise is introduced. Constructing imaging chips and optical component to capture high resolution image is prohibitively expensive and not practical in many cases. Another way is to address to address this problem is to accept the image degradation and use signal processing to post process the captured images, to trade off computation cost with the hardware cost. These techniques are specifically referred as Super- Resolution (SR) reconstruction. SR 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 low-resolution camera.

The goal of SR is to estimate to HR image from one or set of LR images. This inverse problem is inherently ill-posed since many HR can produce the same LR image. SR method can be broadly classified into three classes as Interpolation based methods, learning based methods and reconstruction based methods. Interpolation based methods (Cubic spline for image interpolation, new edge directed interpolation and modified edge directed interpolation) are fast (processing speed) but the results are lack of fine details.

C. Multispectral Satellite Imaging

A multispectral image is one that acquires image data at particular frequencies across the electromagnetic spectrum. Multi spectral satellite imaging is mainly focused on space based imaging. The wavelengths might be separated by various filters or separated by the use of instruments that are very sensitive to particular wavelengths, including the light from frequencies beyond the visible light range, such as the infrared. Multispectral images in remote sensing involves the capturing of visible, near infrared, and short-wave infrared images in several broad wavelength bands. Various materials reflect and absorb differently at various wavelengths. As such, it is easily possible to differentiate among materials by their spectral reflectance signatures as observed in their remotely sensed images, but direct identification is exactly not possible. Multi spectral image provides information that is not available by only exploiting the visible region of the electromagnetic spectrum. It actually provides such things as terrain information over broad areas in an unclassified format. These attributes make Multi spectral imaging easy to share with personnel and organizations that are not privileged with controlled information from national and international assets. Multinational forces, news media and civil authorities can all share the benefits of Multi spectral imaging.

The Linear Imaging Self Scanning Sensor (LISS-III) is a multi-spectral camera that is operating in four spectral bands, three in the visible and near infrared and one in the short wave infrared radiation (SWIR) region which provides data with a spatial resolution of 23.5 meter. The need for improving the resolution of an image is very much essential for the analysis, classification and furthers the recognition of objects. In today's well scientific application areas such as geology and mineral exploration, forest analysis, marine, coastal zone, inland waters and wetlands, agriculture, ecology, urban, the need for a high resolution image is very important. There are also numerous military applications in camouflage, littoral zone mapping, and landmine detection.

The high resolution image can be further achieved by two techniques namely super resolution and image fusion. In the latter, few techniques need PAN and multispectral data. PAN images being expensive, an alternate solution is the super resolution which is cost effective and also produces improved resolution which is up to 3 to 4 times the input image. However one limitation that can be observed with super resolution is the time constraint to generate the super resolved image.

D. Image Quality Assessment

Advances in the digital imaging technology recently, and also the computational speed, networking across wide areas as well as in the storage capacity have resulted in the increased number of digital images, both in terms of still and video [6]. As the digital images are being captured, stored, transmitted, and displayed in various devices, there is a need to maintain image quality. The end user of these various images, in large number of applications, is human observers. The terms image quality and image fidelity is used synonymously, i.e. how close an image is to a given original or reference image [7].

Image Quality Assessment (IQA) plays a fundamental role in the design and evaluation of imaging and image processing systems. Quality Assessment (QA) algorithms can be used to systematically evaluate the performance of different image compression algorithms that attempt to minimize the number of bits required for storage of an image, while maintaining sufficiently high quality of an image [7]. Subjective evaluations are accepted to be the most effective and can be relied on, although quite complicated and expensive, way to assess image quality. Objective IQA measures aim to predict perceived image/video quality by human subjects, which are the ultimate receivers in most image processing applications. Usually one of the images is the reference which is considered to be “original,” “perfect,” or “uncorrupted.” The second image has been modified or distorted in some sense. The output of the QA algorithm is often a number that represents the probability that a human eye can detect a difference in the two images or a number that quantifies the perceptual dissimilarity between the two images [12].

There is need to preserve the image quality of digital images captured, transmitted, displayed and stored. The term image fidelity and image quality is used synonymously, it indicate how best the reconstructed/received image correlates with the original [7]. Image Quality Assessment (IQA) is an essential stage in the design and assessment of image processing algorithms. Quality Assessment (QA) process can be used to evaluate precisely the performance of image reconstruction algorithms that attempt to indicate errors/ noise.

Subjective opinions are accepted to be the most relied and effective, but expensive and complicated way to assess image quality. Objective image quality assessments aim to presume image quality by human subjects, and humans are the ultimate end user in most of the applications.

IQA techniques use one image as reference, it is considered to be perfect/original/uncorrupted and the second image is reconstructed/modified/distorted in some sense. The output of quality assessment techniques will be number that indicates the probability that a human eye can perceive a variation in the two images or it’s a number that assess the perceptual dissimilarity between the reference and reconstructed image[12,14]. The most widely used objective parameters are mean squared error (MSE), Peak Signal-To-Noise Ratio (PSNR), Image Fidelity, Correlation Coefficient, Similarity Measure, etc[5,13].

E. Study area and tools

IRS LISS-III Data Set of Study Area -Belgaum (Latitudes (North) 15°00’ and 17°00’ and Longitudes (East) 74°00 and 75°30’), dated December 31, 2011, Karnataka, India are used as input image and tested with five different techniques.

II. LITERATURE REVIEW

Edge-directed interpolation (EDI) is a method which is to use statistical sampling to ensure quality of an image when you scale it up. The first of the Edge Directed Orientation algorithms developed came from Jan Allebach and Ping Wong [2]. However the Allebach/Wong method does attain the main goals of EDI and it also tends to be overly sensitive and produces more noisy artifacts in the upsampled image. Another method came from Xin Li and Michael Orchard [3] which cured these problems at a minor complication cost over linear interpolation.

Irani and peleg [5] developed their method based on the principle of reconstruction of a 2D object from its 1D projection in various medical diagnostics. Here they carried out an iterative way of super resolving an image and thereby considering the difference in error between observed low resolution images and corresponding stimulated images obtained from high resolution image which was minimized. The concept of super resolving from a single image was put forth by Schultz and Stevenson.

Sun et al. used the former Gradient Profile Prior which was learned from a large number of natural images to obtain sharp edges at much large magnifications. However Glasner et al. exploited the recurrence of patches and constructed a number of LR/HR training pairs by searching them through an image pyramid.

Muhammad Murtaza Khan, et.al., [22]In this paper, a method is proposed to assess the fusion quality at high resolution by making use of modulation transfer function filters in the frame works of Wald's spectral consistency protocol and Zhou's spatial standard protocol. The results are compared with the recently proposed QNR quality index. This does not require a reference high resolution multispectral image.

Yongnian Zeng, et.al, [24] the fusion of panchromatic and multispectral satellite images is an important issue in many remote sensing areas, especially in urban area. The popular image fusion methods in remote sensing community usually distort the spectral quality. To reduce this spectral distortion, some image fusion techniques have been advanced. This paper focusses the issue in quality assessment of fused images from three recently developed methods. These are synthetic variable ratio (SVR), smoothing filter-based intensity modulation (SFIM) and Gram- Schimdt transforms (GS).

Andrea Garzelli and Filippo Nencini [20] this letter presents a novel image quality index which extends the Universal Image Quality Index for monochrome images to multispectral and hyper spectral images through hyper complex numbers. The index is based on the computation of the hyper complex correlation coefficient between the reference and examined images, which together measures distortions having to do with space and spectra. The tested results, both from true and simulated images are presented on space borne and airborne visible images. The experiments prove exact measurements of inter and intra band distortions even when anomalous pixel values are concentrated on few bands.

Christophe Charrier, et.al., [21] A crucial step in image compression is the evaluation of image performance, and more precisely the possible way to measure the final quality of the squeezed image. For measuring the performance, the variation between the subjective ratings and the degree of compression is performed between rated image quality and considered algorithm. Nevertheless, the local variations are not well taken into consideration. The author uses the recently introduced Maximum Likelihood Difference Scaling (MLDS) method to quantify suprathreshold perceptual differences between pairs of images and examine how perceived image quality estimated through MLDS changes the compression rate. This approach circumvents the limitations inherent to subjective rating methods. Zhou, et.al, [25] this chapter introduces the basic ideas and algorithms of structural approaches for assessment of image quality. It describes the concepts and thethe SSIM index. It also takes into account, the image synthesis-based performance evaluation algorithm in the image space. The paper demonstrates that image distortions along different directions in the image space have different insight meanings. The structural approaches attempt to separate the directions associated with structural distortions from those with non-structural distortions. This differentiation gives a new coordinate system in the space of an image which is not permanent as in traditional image decomposition frameworks (e.g., Fourier and wavelet types of transforms), but adjusted to the underlying image tructures.

Peter Longhurst and Alan Chalmers [23] with modern graphical hardware, it is not yet possible to achieve high fidelity renderings of complex scenes in real time. Often, as these images are produced for human observers, it is exploited that the human eye is good, but not that good. In particular, it may be possible to render parts of an image at high quality and the rest of the scene at lower quality without the user being aware of this unlikeliest. Image quality assessment approaches, such as the Daly IQA model, provide a measure of the perceptual quality difference between image pixels. The paper presents a psychophysical evaluation of an image quality metric and investigates how such models can be developed to rapidly determine the parts of the scene with the most noticeable perceptual difference.

III. SUPER RESOLUTION IMAGE RECONSTRUCTION

Proposed SR technique algorithm represented in figure 1,

Step 1. Input the test satellite image.

Step 2. Separate the test image into 3 component colors (R, G and B) and store them separately

Step 3. Divide each component color layer into NxL small segments called "cells" of some specific dimension Step 4. The super resolution algorithm is then applied to each individual cell.

Step 5. After applying super resolution to L such cells of N^{th} row, all the L cells are horizontally concatenated to form a horizontal strip.

Step 6. After doing step 5 for all the N rows, all the N horizontal strips thus obtained are concatenated vertically to form the super resolved image of the input test image.

Step 7. The results are then displayed in the figure window for comparison

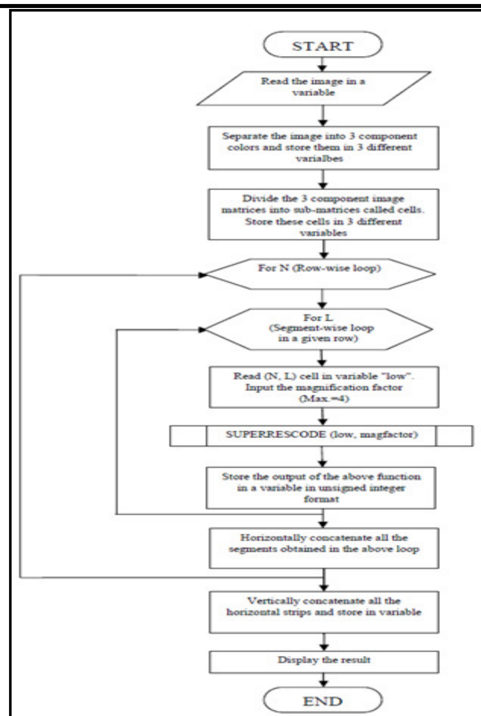


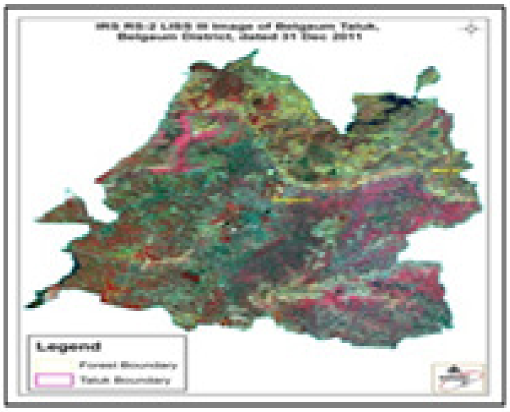
Fig. 1. Flow chart of proposed SR method (Our Method)

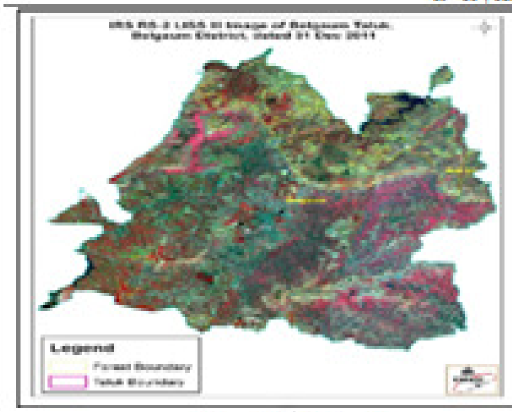
IV. SR Comparative Analysis

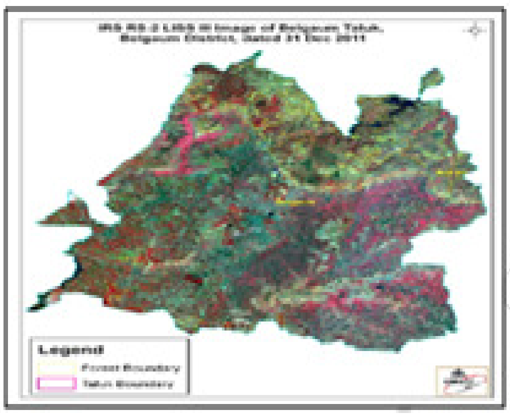
SR comparative analysis is summarized in Table I, the proposed method outperformed over other four techniques with better PSNR and MSE. This demonstrates that our method is good both at speckle noise suppression and image detail preservation figure 2-7.

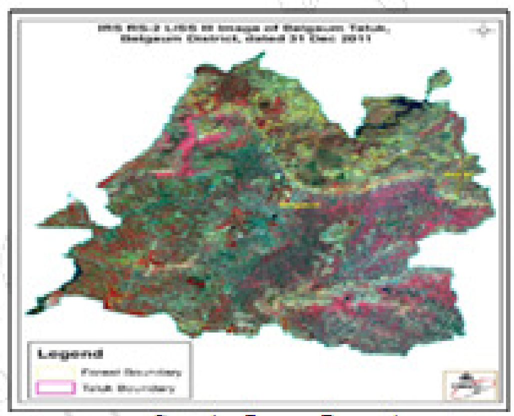
TABLE I. COMPARATIVE ANALYSIS OF ALGORITHMS

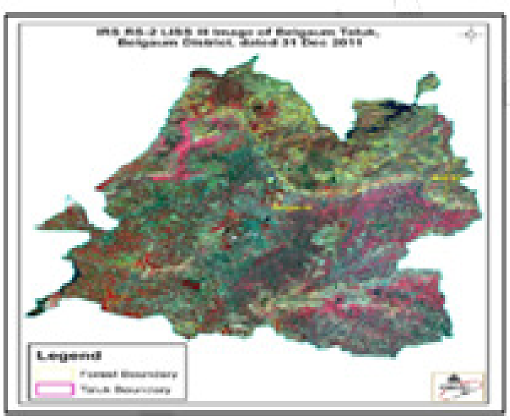
Method	IRS LISS III Multispectral satellite Input Image: Dimension 899X1163						
	SR Image	Time taken to process	MSE	PSNR	Image Fidelity	Correlation coefficient	Similarity measure
Bicubic	1798X2326	133.6189	125.1397	43.9907	0.9969	0.9985	1.0027
Example Based	1798X2326	432.5896	71.2858	46.4346	0.9982	0.9991	1.0030
New Edge Directed	1798X2326	1071.7106	200.5067	41.9433	0.9951	0.9975	1.0020
Gaussian Process Regression	2697X3489	22803.5682	64.5527	44.8655	0.9984	0.9992	1.0030
Our Method	2697X3489	322.8704	64.3087	46.8819	0.9984	0.9992	1.0030

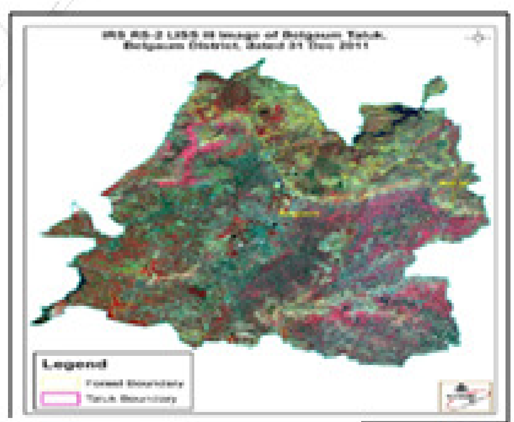












V. IQA COMPARATIVE ANALYSIS

In Table II, when we consider Salt and Pepper noise. We see that the values are predicting the quality in a positive way as the value of the PSNR is high enough. Seeing the table, it can be concluded that salt and pepper noise predicts Peak Signal to Noise Ratio (PSNR) of the image in a better way. The amount of information present in the image is not affected much when PSNR is considered with respect to salt and pepper noise.

TABLE II. METRICS FOR ALL THE IMAGES WHEN SALT AND PEPPER NOISE IS CONSIDERED

IRS LISS III Multispectral satellite Input Image	**Metrics Images-** Salt and Pepper noise is considered					
	MSE	**RMSE**	**PSNR**	**Entropy**	**Lumi Masking**	**Error Pooling**
Belgaum	0.20497	0.45274	Infinity	4.7584	Infinity	5.3014e^-005
	Metrics Images- Poisson noise is considered					
	MSE	**RMSE**	**PSNR**	**Entropy**	**Lumi Masking**	**Error Pooling**
	0.051446	0.22682	61.0867	6.3008	0.009664	5.1812e^-005

	Images HVS Models- Gaussian noise is considered						
	VDP	**TEO & HEEGER**	**WATSON'S DCT**	**PIC**	**SARNOFF JND**	**VSNR**	**SSIM**
Belgaum	0.9986	0.7252	0.9553	90.7643	0.9945	18.9547	0.5301

	Images Theoretic Models	
	IFC	**VIFC**
Belgaum	0.9051	0.8886

VI. CONCLUSION

In image processing algorithms spatial resolution, brightness resolution and temporal resolution are significant features and if the image is of high resolution it may used in number of applications, high resolution helps in identification and classification process more precisely. This paper presents four super resolution techniques Patch based Processing Method, Gaussian Process Regression, Bicubic Interpolation and Edge Directed Orientation Method for single frame image. A image has been given as an input to these three techniques and change in the resolution has been observed. Patch based Processing technique generated superior results referring processing speed, perceptual quality and time. There is still scope to improve the processing time, noise model and noise sensitivity of super resolution algorithm.

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