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Super Resolution Image Generation Using Wavelet Domain Inter Polation with Edge Extraction Via A Sparse Representation

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ABSTRACT

This letter addresses the problem of generating a super-resolution (SR) image from a single low-resolution (LR) input image in the wavelet domain. To achieve a sharper image, an intermediate stage for estimating the high-frequency (HF) sub bands has been proposed. This stage includes an edge preservation procedure and mutual interpolation between the input LR image and the HF sub band images, as performed via the discrete wavelet transform (DWT). Sparse mixing weights are calculated over blocks of coefficients in an image, which provides a sparse signal representation in the LR image. The entire sub band images are used to generate the new high-resolution image using the inverse DWT. Experimental results indicated that the proposed approach outperforms existing methods in terms of resolution This stage includes an edge preservation procedure and mutual interpolation between the input LR image and the HF sub band images, as performed via the discrete wavelet transform (DWT). Sparse mixing weights are calculated over blocks of coefficients in an image, which provides a sparse signal representation in the LR image. All of the sub band images aroused to generate the new high-resolution image using the inversed. Experimental results indicated that the proposed approach outperforms existing methods in terms of objective criteria and subjective perception improving the image resolution

INTRODUCTION

THE images and video sequences that register from radar, ptical, medical and other sensors and that are presented on high-definition television, in electron microscopy, etc., are obtained from electronic devices that use a variety of sensors. Therefore, a preprocessing technique that permits enhancement of image resolution should be used. This step can be performed by estimating a high-resolution (HR) imagefrommeasurements of a low-resolution (LR) imagethatwere obtained through a linear operator that forms a degraded version of the unknown HR image, which was additionally contaminated by an additive noises a sub sampling operator that should be inverted to restore an original image size, and this problem usually should be treated as an ill-posed problem. In remote sensing monitoring and navigation missions with small airborne or unmanned flying vehicle platforms, LRsensors with simple and cheap hardware, such as unfocused fractional SAR systems, optical cameras, etc., and using the Manuscript received The authors are with the School of Mechanical and Electrical Engineering(ESIME) Culhuacán Unit, Institute Polytechnic National, 07738 Mexico City, Mexico (e-mail: charomi0880@yahoo.com.mx; vponomar@ipn.mx).Color versions of one or more of the figures in this paper are available online Digital Object Identifier 10.1109/LGRS.2014.2308905onboard processors are attractive. However, such cheap sensors or fractal synthesis mode inevitably sacrifices spatial resolution. The system could also suffer from the uncertainties that are attributed to random signal perturbations, imperfect system calibration, etc. Therefore, the SR algorithms that are the cost-effective decisions have an important application in the pro-cussing of satellite or aerial images obtained by radar or optical sensors [1], [2].The wavelet technique as a simple sparse representation also plays a significant role in many image processing applications, in particular in resolution enhancement, and recently, many novel algorithms have been proposed [3].Prior information on the image sparsely has been widely used for image interpolation [4]. The principal idea behind the restriction of the sparse SR algorithms is that the HR results can be improved by using more prior information on the imageproperties.The predominant challenge of this study is to employ an approach that is similar to the approach of these wavelet-based algorithms, accounting for both spatial and spectral wavelet pixel information to enhance the resolution of a single image. The principal difference of the novel SR approach in com-parson with existing methods consists in the mutual interpolation via Lenclos [5], [6] and nearest neighbor interpolation (NNI) techniques for wavelet transform (WT) high-frequency (HF) sub band images and edge extracting images via discrete wavelet transform (DWT); additionally, an adaptive directionally image interpolation is computed by estimating sparse image mixture models in a DWT image. To obtain robustness for these process in presence of noise, the novel framework uses special demising filtering, employing the nonlocal means (NLM)technique for the input LR image [7].Finally, all of the subbandimages are combined, reconstructing via inverse DWT

(IDWT)the output HR image that appears to demonstrate superiority of the designed algorithm in terms of the objective criteria and subjective perception (via the human visual system), in comparison with the best existing techniques. To justify that the novel algorithm called super resolution using wavelet domain interpolation with edge extraction and sparse representation (SR-WDIEE-SR) has real advantages, weave compared the proposed SR procedure with other similar techniques, such as the following: Demirep - Anbarjafari Super Resolution [8], Wavelet Domain Image Resolution Enhance-mint Using Cycle-Spinning [9], Image Resolution Enhance-mint by using Discrete and Stationary Wavelet Decomposition The technology of image magnification focuses on how to magnify a low resolution (LR) image and at the same time recover some high resolution (HR) details. The methods of this technology can be divided into three categories: the method based on up scaling the method based on reconstruction and the method based on learning Some methods based on up scaling, such as bilinear and bucolic interpolation (BI) are popular since they have low computational complex, but they always produce blurring edges and suffer from artifacts since they use the invariant kernels for all kinds of local textures. Methods based on reconstruction aim at reconstructing the HR image by imitating the inverse process of degradation these methods rely on the rationality of the reconstructing model. The methods based on up scaling and reconstruction has smaller memory space costs than the learning-based methods in most of the cases. But it is difficult to use some simple mathematical models to fit the sophisticated natural conditions. This makes these methods cannot recover many texture details. The learning-based methods are more flexible to deal with the problem they use the training images to learn the relationship between the HR and LR images, and many existing works have demonstrated their good effect for the high magnification factors

Image super-resolution (SR) are techniques aiming estimation of a high-resolution (HR) image from one or several low-resolution (LR) observation

Proposed algorithm

If the input LR image has noise, how could we deal with it? An idea that flashed into the mind may be firstly demising the LR image and then magnify it. But it is difficult to be executed, since the textures are dense and incomplete in the LR image. Therefore, we propose an algorithm to solve this problem. The framework of the proposed algorithm is shown in A TV regularization-based algorithm is employed to simultaneously accomplish magnification and demising at first. The details of the proposed TV regularization model will be described in

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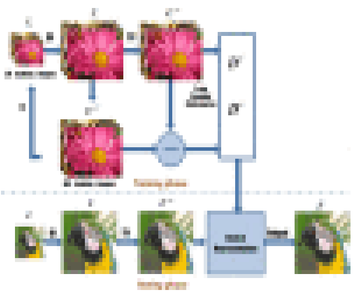
Section 2.1. After the TV regularization, some texture details are damaged. We use an OCDT algorithm to compensate the texture details. The details of this step will be shown in Section



```
%% Visualization of audio spectrum frame by frame
% Create System objects and initialize them
Microphone    = dsp.AudioRecorder;
Speaker       = dsp.AudioPlayer;
SpecAnalyzer = dsp.SpectrumAnalyzer;
% Process frame-by-frame in a loop
tic;
while (toc < 30)
    audio = step(Microphone);
            step(SpecAnalyzer,audio);
            step(Speaker, audio);
end
```

MULTIRESOLUTION DIRECTIONAL TRANSFORMS

One of the main goals of a transform representation is to determine efficient linear expansions for images. Efficiency is generally measured in terms of the number of elements needed in a linear expansion. To quantify the number of elements needed for a linear expansion, image models are employed. Commonly, images are considered as uniform 2D functions separated by singularities (e.g., edges). The singularities them-selves are modeled as smooth curves. In the past decades, developments in applied harmonic analysis have provided many useful tools for signal processing. Wavelets are good at isolating singularities in 1D. Extending wavelets to 2D makes

They well adapted to capture point-singularities. But in natural images, there are mostly line- or curved- singularities (e.g., directional edges). These are also known as anisotropic features as they are dominant along certain directions. To capture such features, there has been extensive study in constructing and implementing directional transforms aiming to obtain sparse representations of such piecewise smooth data. The curvelettransform is a directional transform which can be shown to provide optimally sparse approximations of piecewise smooth images However, curve lets offer limited localization in the spatial domain since they are band limited. Also, they are based on rotations which introduce difficulties in achieving consistent discrete implementation. Contour lets are com-partly supported directional elements constructed based on

directional filter banks [17]. Directional selectivity in this approach is artificially imposed by a special sampling rule of filter banks which often causes artifacts. Moreover, no theoret-icalguarantee exists for sparse approximations for piecewise smooth images. Recently, a novel directional representation system known as shear lets has emerged, which provides unified treatment of continuous as well as discrete models, allowing optimally sparse representations of piecewise smooth images [25, 29]. This simplified model of natural images, which emphasizes anisotropic features, most notably edges, is found to be consistent with many models of the human visual system [26]. The framework proposed in this paper inapplicable for all these transforms, although shear lets is ob-served to provide the best performance among the consideredtransforms.Multi-resolution directional transforms can also be seen as filter banks. The decomposition is implemented using an analysis filter bank, while the reconstruction is implemented using a synthesis filter bank. One branch of the filterbankis designed as a low pass channel that captures a coarse representation of the input signal followed by band- or high-

Image Super-resolution

images, which offer the promise of overcoming someoftheinherent resolution limitations of low-cost imaging sensors (e.g., cell phone cameras or survey-lance cameras), and allow better utilization of the growing capability of HR displays (e.g., HD LCDs).Conventional super-resolution approaches normally require multiple LR inputs of the same scene with sub-pixel motions. The SR task is thus cast as an inverse problem of recovering the original HR image by fusing the LR inputs, based on reasonable assumptions or prior knowledge about the observation model. However, SR image reconstruction is typically severely ill-conditioned because of the insufficient number of observations and the unknown registration parameters. Various regularization techniques are therefore proposed to stabilize the inversion of this ill-posed problem [13]–[15].However, the performance of conventional approaches is only acceptable for small up scaling factors (usually less than 2) [16], leading to the development of later example-based learning approaches, which aim to learn the co-occurrence prior between the HR and LR image local structures from an external raining database [17]–[19]. This training database is usually required to contain millions of HR/Linage patch pairs in order to represent a generic image well, which makes the algorithms computationally intensive. Instead of relying on an external database, several recently proposed approaches exploit the self-similarity properties of local image patches within and across different spatial scales in the same image for super-resolution [20]–[24]. These approaches either need a separate deploring process [20], [23], which is ill-posed and requires parameter tuning by itself, or relies too much on local image singularities,e.g., edges and corners, thus generating super-resolution results which are not photo realistic [22], [24].Motivated by the recent compressive sensing theories [10], Yanked align [8], [25] proposed to use sparse representation to recover the HR image patch. The method can generate both photo realistic textures and sharp edges from a single input image. However, the joint dictionary training method proposed in [8]does not guarantee that the sparse representation of a LR image patch can well reconstruct its underlying image patch. We will show that our coupled dictionary learning method can overcome this problem and demonstrate superior performance both qualitatively and quantitatively. Despite its strength in sparse signal recovery, sparse representation cannot be calculated in an efficient way due to the1-norm minimization, which hinders its application in many real time scenarios with constrained computational resources. For example, it typically takes more than one minute to magnify air image of size128×128by a factor of2, which is intolerable to most users. In this paper, to enable the practical application of our sparse recovery based super-resolution in consumer photo editing,e.g.,inPhotoshopTM, we further propose an efficient implementation of our algorithm based on two strategies:

IMAGE RESOLUTION ENHANCEMENT METHOD USING SWTAND DWT

The main loss in image resolution enhancement by using interpolation is on its highfrequencycomponents (i.e., edges), which is due to the smoothing caused by interpolation. Edges plays very important role in image. To increase the quality of the super resolved image, it is essential to preserve althea edges in image. In [7] work, DWT has been employed in order to preserve the high frequency components of the image (i.e. edges). The redundancy and shift invariance of the DWT mean that DWT coefficients are inherently interpolable.In this correspondence, one levelDWT (with Daubechies 9/7 as wavelet function) is used to decompose an input image into different sub band images. Three high frequency sub bands (LH, HL, and HH) contain the high frequency components of the input image (i.e. edges).In this technique, bucolic interpolation with enlargement factor of 2 is applied thigh frequency sub band images. Information loss occur due to down sampling in each of the DWT sub bands cause din the respective sub bands. That is why SWT (Stationary Wavelet Transform) is used to minimize this loss The SWT is an inherently redundant scheme as the output of each level of SWT contains the same number of samples as the input –so for a decomposition of N levels there is a redundancy of N in the wavelet coefficients. The interpolated high frequency sub bands and the SWT high frequency sub bands have the same size which means they can be added with each other. The new corrected high frequency sub bands can be interpolated further for higher enlargement. Also it is known that in the wavelet domain, low pass filtering of the high resolution image produce the low resolution image. Another word, low frequency subbed is the low resolution of the original image. Therefore, instead of using low frequency subbed, which contains less information than the original high resolution image, Has an Demirep and Gholamreza Anbarjafari [7] are Using the input image for the interpolation of low frequency subbed image.Thequality of thesuperresolved image increases using input image instead of low frequencysubband. Illustrates the block diagram of the used image resolution enhancement technique. By interpolating input image by3, and high frequency sub bands by 2 and in the intermediate and final interpolation stages respectively, and then by applying IDWT, as illustrated in , the output image will contain sharper edges than the interpolated image obtained by interpolation of the input image directly. This is due to the fact that, the interpolation of isolated high frequency components in high frequency sub bands and using the corrections obtained by adding high frequency sub bands of SWT of the input image, will preserve more high frequency components after the interpolation than interpolating input image directly

PROPOSED ALGORITHM

displays the flowchart of proposed algorithm for single image super resolution that is based on the algorithm presented in [11]. Here some changes have been done in original algorithm of [11] as down sampling method is changed, new up sampling algorithm is used and wavelet based demising algorithmic Below each step of flowchart is explained in detail

Down sampling to get low-resolution image

To acquire the low-resolution image, take high-resolution image and convert it into low-resolution image using below method (Figure 2). Here block of 2 x 2 is chosen and 1 pixel of low-resolution image for every 4 pixel of high-resolution image is derived.

Up sampling of the image

Method proposed in [9] is used for up sampling. Some of the changes have been made in original method like instead of Bucolic, Bucolic smoother method of Photoshop cs5 (as shown in figure) is used, demising algorithm is applied on HH band and HAAR wavelet is chosen and instead of Cohen-Daubechies-Feauveau (CDF) 9/7 wavelet as a mother wavelet transform because HAAR wavelet is computationally fast. Many other wavelets are available which provide better results like sym; db4 etc. but all require more time for computation. During experiment on program using HAAR, it has taken 8.37 seconds while DB4 has taken 9.13 seconds. New modified algorithm for image up sampling is shown in the figure. Below explained is the complete method of image up-sampling.

Gaussian Filter and Down sampling

After up sampling due to point spread function (PSF) image can be look blurred little bit. So Gaussian filter merely work like smoothing kernel. As the blurred effect is very low or ignorable Gaussian filter applies only once. Instead of Gaussian filter, winey filter can be used or Iterative blur DE convolution, Lousy Richardson algorithm can be used[6]. Same as step1 using bucolic sharper algorithm image is down-sampled.

Reconstruction and up sampling the error

In this stage of algorithm error is calculated between original low-resolution image of step 1 and down sampled image of step 4. This is the most important part of algorithm because the error that we find in this stage is used as the correction parameter in getting super resolution image and also used for refining coefficients of sub bands. By experiments it has been observed that after three to four iteration error becomes so small that it can be neglected

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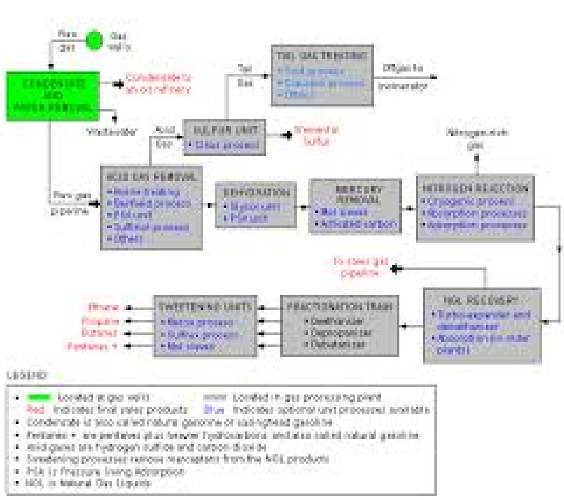
Resolution enhancement technologies

Are methods used to modify photo masks for integrated circuits (ICs) to compensate for limitations in the lithographic processes used to manufacture the chips? Traditionally, after an IC design has been converted into a physical layout, the timing verified, and the polygons certified to be DRC-clean, the IC was ready for fabrication. The data files representing the various layers were shipped to a mask shop, which used mask-writing equipment to convert each data layer into a corresponding mask, and the masks were shipped to the fib where they were used to repeatedly manufacture the designs in silicon. In the past, the creation of the IC layout was the end of the involvement of electronic design automation

.

RET Technique	Manufacturability Improvement
Scattering Bars	Sub resolution assist features that improve the depth of focus of isolated features.
Phase-shift Mask	Etching quartz from certain areas of the mask (alt-PSM) or replacing Chrome with phase shifting Molybdenum Silicate layer (attenuated embedded PSM) to improve CD control and increase resolution
Double or Multiple Patterning	Involves decomposing the design across multiple masks to allow the printing of tighter pitches.



THEORETICAL BACKGROUND AND IMPLEMENTATION

Preprocessing of MODIS Images

The calibrated and geo-referenced MODIS data is directly available, but the products are available in sinusoidal (SIN) projection grid. Therefore, band1 and band 2 of Medicare geometrically converted into UTM projection using ENVI4.8 software. An important problem in the use of optical images is occurrence of clouds. The land surfaces of those areas can be seen only which are not affected by the presence of clouds. The preprocessed MODIS data consists of two bands one in the near infrared (NIR) and other is red wavelength. These two bands may be fused or processed individually as per the application [16]

Vegetation Parameter

Surface reflectances at two or more wavelengths are combined to produce vegetation indices (VIs) which are designed to emphasize particular feature of vegetation. There is quite a lot of vegetation indices published in the scientific literature; each accentuates a particular vegetation property. ENVI4.8 is used to calculate the NDVI values of the image. NDVI is used to analyze the vegetation cover over a region. The Normalized Difference Vegetation Index (NDVI) is mainly used to characterize the vegetation regions, as it isalmostlinearly associated to the vegetation abundance. NDVI is defined as the ratio of the difference and sum of the spectral response at thenearinfrared (NIR) wavelength and red wavelength as [17]

Reconstruction and up sampling the error

In this stage of algorithm error is calculated between original low-resolution image of step 1 and down sampled image of step 4. This is the most important part of algorithm because the error that we find in this stage is used as the correction parameter in getting super resolution image and also used for refining coefficients of sub bands. By experiments it has been observed that after three to four iteration errors becomes so small that it can be neglected

.

Up sampling the error is most important step of the proposed algorithm.

Forreconstructingsuperresolution image, error must be back projected and for that error matrix must be up-sampled to meet super resolution image. Bucolic smoother algorithm of Photoshop cs5 is used for up-sampling error matrix

Back projecting error

Finally error matrix generated in step 6 is added with high-resolution image generated in step 3. Repeat the above procedure as shown in the figure till we acquire satisfactory results. Within three iterations appropriate result comes.

QUALITY ASSESSMENT PARAMETERS

Technique	Correlation Coefficient	RMSE	PSNR
Proposed Algorithm	0.99	0.0066	40.5850
BicubicInterpolation	0.9954	0.0076	39.3750
Bilinear Interpolation	0.9887	0.0119	35.487

EXPERIMENT AND RESULT

Experiment of proposed algorithm is performed on the computer with configuration of Intel i3 processor, 4GB RAM and 512MB Vida graphics card. For performance evaluation of algorithm, PNSR ratio and visual quality are considered as parameters. The PSNR is defined as: PSNR = 20 · log 10(MAX i /√MSE). Comparison of cubic interpolation, new edge directed interpolation [33], wavelet zero padding (WZP) same as image up-sampling using DWT [55], algorithm proposed in [11](denoted as FF) and proposed method have been done for six different images of line, Mona Lisa, Baboon, Pepper, Dog, PS logo and some textures (A1 to A6). For doing up sampling in algorithm, Photoshop is used. Same algorithm is also implemented in MATLAB without using Photoshop (used bucolic interpolation function). It gives almost same result as manual method. Sample MATLAB code for proposed algorithm is also given.

Apply Bucolic smoother interpolation of Photoshop cs5 as expounded in step1 on low-resolution image that produces up-sampled image. On these up-sampled image, apply DWT which produces four sub bands of size m x n each. Now LH, HL and HH sub bands produced by DWT and by SWT are incremented to correct the estimated coefficients.

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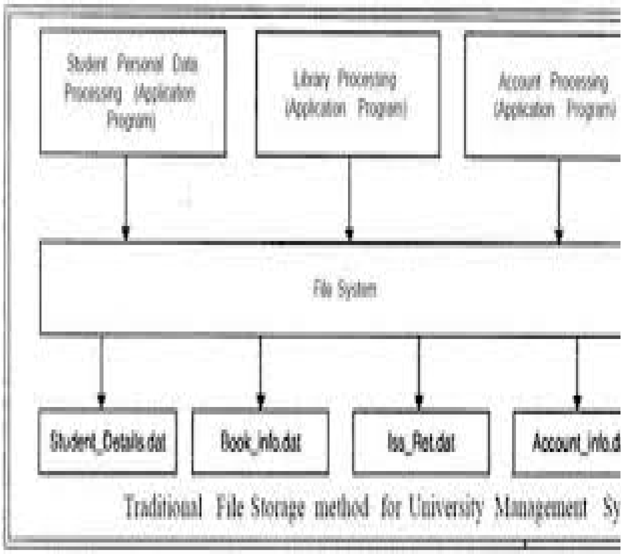

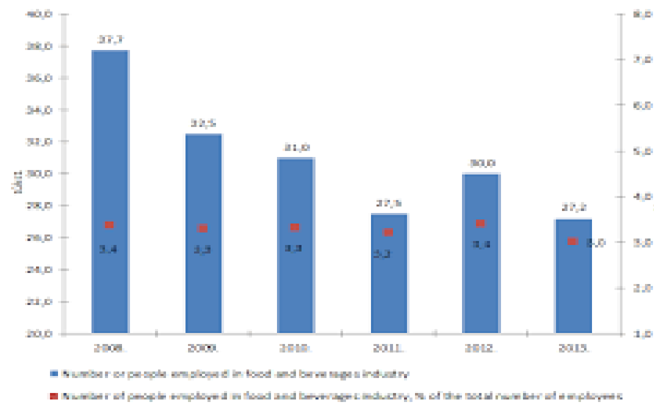

Table 1. Comparison of different methods using PSNR ration (512 x 512 resolutions)

	Bicubic	NEDI	WZP	FF	roposed Method
Lena	32.549	31.479	31.725	32.586	32.61
Mona Lisa	29.428	27.917	27.944	29.624	29.589
Baboon	32.842	31.619	31.925	32.862	32.933
PS logo	26.172	25.688	26.018	26.288	26.216
Dog	26.656	25.438	25.912	26.731	26.693
Peppers	28.771	27.533	27.881	28.711	28.787
A1	30.592	29.838	30.189	31.472	1.639
A2	29.852	29.337	29.762	30.278	30.372
A3	30.992	30.673	30.936	31.173	31.386
A5	31.750	30.753	30.826	32.037	32.139
A6	32.283	31.161	31.378	32.420	32.639

LITERATURE SERVEY

Previously numerous of techniques are used for resolution enhancement of images in different

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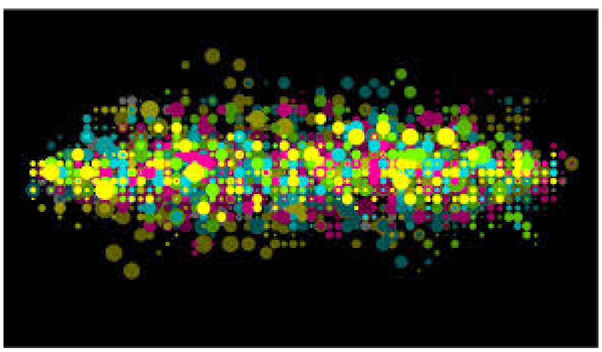
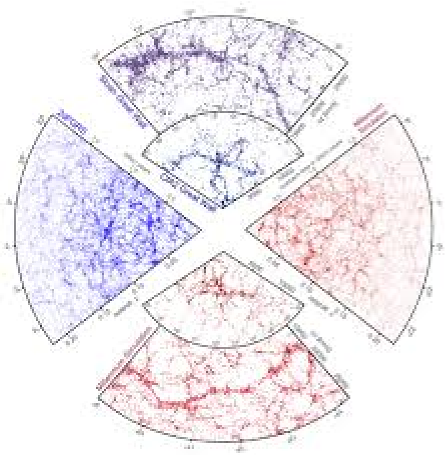
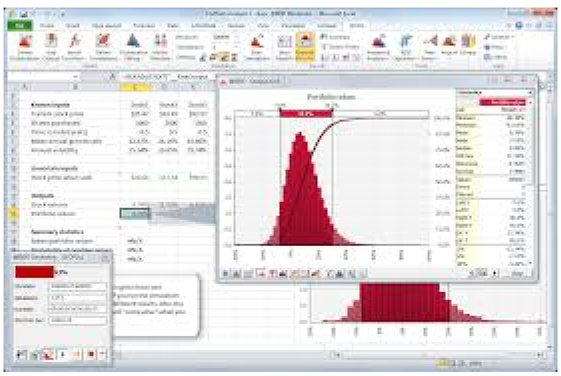
applications. As discussed earlier, images such as satellite images consists of important details that plays vital role in many image processing applications and hence resolution enhancement is must for the same. Many of the researchers have proposed different methods to increase quality of images in accordance with resolution.



SIMULATION OUTPUT AND DISCUSSION

This section reports the results of the applied mathematics simulations andtheperformanceanalysisthat'sconducted via objective metrics (Peak signal-to-noise ratio, Mean square Error, andStructuralSimilarity Index Measure) [17]. additionally, a subjective visual comparison of the SR pictures performed by different algorithms was used and so created it to evaluate the performance of the analyzed techniques during different mane Numerous aerial optical and radar measuring system satellite pictures from [13] and [14], notably Aerial-A and SAR-B pictures of various nature and physical characteristics, were studied applying the designed and higher existing SRprocedures. In simulations, the pixels of the LR image are obtained by downsamplingthe original time unit image by an element of four in every axis. within the demising stage, the NLM filter from (2) was applied, the neighborhood Q was found within the simulation as 5×5five pixels, and the parameter δ = two was chosen. In this letter, the subsequent families of classic waveletfunctionsis used lifting wavelet. In the Aerial-A image , it's straightforward to envision higher performance in accordance with the target criteria and via subjective beholding in SR once the planned algorithmic programs-IGFL-Wits utilized with the , demonstrating better preservation of the fine feature within the zoomed part of the image. it's higher sharpness and fewer smoothing at the sides, preventing pixel block (known as jaggier), blurreddetails, and ringing artifacts around edges.





CONCLUSIONS AND FUTURE WORK

Proposed algorithm uses advantage of both wavelet and spatial domain. PSNR ratio and visual quality of images are also shows the effectiveness of algorithm. Algorithm gives almost same result as algorithm proposed in [11]. Proposed algorithm is faster. Some more work on up sampling algorithm will surly improves result. In future more work on wavelet domain and texture-based up sampling will be conducted and comparison will be done to see which algorithm work better for which kind of image.

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