ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com

International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 4, Special Issue 3, February 2017

HIGHLY ADAPTIVE IMAGE RESTORATION TECHNIQUE FOR COMPRESSIVE SENSING

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Abstract: Traditional Patch Based Sparse Reprensentation used for image restoration suffer from two problems. First, it has to solve a large optimization problem with high computational complexity in dictionary learning. Second, in dictionary learning and sparse coding each patch is considered alone, which neglect the releationship among patches and provide inaccurate sparse coding coefficients. In traditional patch based patch representation it uses twice the frequency samples for sampling i.e. the Nyquist rate. In this paper we introduce concept of Group Based Sparse Representation, it consist of nonlocal sparse with similar structure and attain sparse reprensentation for the images. It is designed with low complexity self adaptive dictionary learning for each group. Split Bregman based technique is introduce to make the GSR robust and solve the Proposed GSR driven. In this method the samples are taken below the nyquist rate.

Key words: PSNR, FSIM , Group based sparse representation

I.INTRODUCTION

An image is an array, or a matrix, of square pixels (picture elements) arranged in columns and rows in a (8-bit) greyscale image each picture element has an assigned intensity that ranges from 0 to 255. A grey scale image is what people normally call a black and white image, but the name emphasizes that such an image will also include many shades of grey.

1.1 COMPRESSIVE SENSING

It is a signal processing technique for efficiently acquiring and reconstructing a signal by finding solutions to undetermined linear system. It is based on the principle that, through optimization, the sparsity of the signal can be exploited to recover it from for few samples than require by the Shannon – Nyquist sampling theorem.

Two conditions under which recovery is possible.1)The first one is sparsity, which requires the signal to sparse in some domain. The second one is incoherence which is applied through the isometric property which is sufficient for sparse signals.

2)compressive sensing (CS) has attracted considerable attention in areas of applied mathematics, computer science, and electrical engineering by suggesting that it

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may be possible to surpass the traditional limits of sampling theory. CS builds upon the fundamental fact that we can represent many signals using only a few non-zero coefficients in a suitable basis or dictionary. Nonlinear optimization can then enable recovery of such signals from very few measurement. We are in the midst of a digital revolution that is driving the development and deployment of new kinds of sensing systems with ever-increasing fidelity and resolution. The theoretical foundation of this revolution is the pioneering work of Kotelnikov, Nyquist, Shannon, and Whittaker on sampling continuous-time band-limited signals. Their results demonstrate that signals,images, videos, and other data can be exactly recovered from a set of uniformly spaced samples taken at the so-called Nyquist rate of twice the highest frequency present in the signal of interest. Capitalizing on this discovery, much of signal processing has moved from the analog to the digital domain and ridden the wave of Moore's law. Digitization has enabled the creation of sensing and processing systems that are more robust, flexible, cheaper and, consequently, more widely used than their analog counterparts. As a result of this success, the amount of data generated by sensing systems has grown from a trickle to a torrent. Unfortunately, in many important and emerging applications, the resulting Nyquist rate is so high that we end up with far too many samples.

1.1.2 COLOR SPECIFICATION

The Y, Cb, and Cr components of one color image are defined in YUV color coordinate, where Y is commonly called the luminance and Cb, Cr are commonly called the chrominance. The meaning of luminance and chrominance is described as follows

Luminance: received brightness of the light, which is proportional to the total energy in the visible band.

Chrominance: describe the perceived color tone of a light, which depends on the wavelength composition of light chrominance is in turn characterized by two attributes – hue and saturation.

hue: Specify the color tone, which depends on the peak wavelength of the light

saturation: Describe how pure the color is, which depends on the spread or bandwidth of the light spectrum

The RGB primary commonly used for color display mixes the luminance and chrominance attributes of a light. In many applications, it is desirable to describe a color in terms of its luminance and chrominance content separately, to enable more efficient processing and transmission of color signals. Towards this goal, various three-component color coordinates have been developed, in which one component reflects the luminance and the other two collectively characterize hue and saturation. One such coordinate is the YUV color space. The $[Y\ Cb\ Cr]^T$ values in the YUV coordinate are related to the $[R\ G\ B]^T$ values in the RGB coordinate by

$$\begin{pmatrix} Y \\ Cb \\ Cr \end{pmatrix} = \begin{pmatrix} 0.299 & 0.587 & 0.114 \\ -0.169 & -0.334 & 0.500 \\ 0.500 & -0.419 & -0.081 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix} + \begin{pmatrix} 0 \\ 128 \\ 128 \end{pmatrix}$$

Similarly, if we would like to transform the YUV coordinate back to RGB coordinate, the inverse matrix can be calculated from the above equation, and the inverse transform is taken to obtain the corresponding RGB components.

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1.1.3 THE FLOW OF IMAGE COMPRESSION CODING

Image compression coding is to store the image into bit-stream as compact as possible and to display the decoded image in the monitor as exact as possible. Now consider an encoder and a decoder as shown in Fig. 1.2.2. When the encoder receives the original image file, the image file will be converted into a series of binary data, which is called the bit-stream. The decoder then receives the encoded bit-stream and decodes it to form the decoded image. If the total data quantity of the bit-stream is less than the total data quantity of the original image, then this is called image compression. The full compression flow is as shown in Fig. 1.2.2.

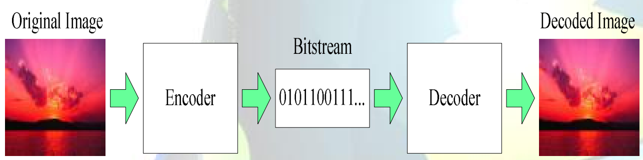

Fig 1.1.2 The basic flow of image compression coding

The compression ratio is defined as follows:

$$Cr = \frac{n1}{n2},$$

where$n1$ is the data rate of original image and $n2$ is that of the encoded bit- stream.

In order to evaluate the performance of the image compression coding, it is necessary to define a measurement that can estimate the difference between the original image and the decoded image. Two common used measurements are theMean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR), f(x,y) is the pixel value of the original image, and f'(x,y)is the pixel value of the decoded image. Most image compression systems are designed to minimize the MSE and maximize the PSNR.

$$MSE = \sqrt{\frac{\sum_{x=0}^{W-1}\sum_{y=0}^{H-1}[f(x,y)-f'(x,y)]^2}{WH}}$$

$$PSNR = 20\log_{10}\frac{255}{MSE}$$

1.1.4 JPEG – Joint Picture Expert Group

In the Encoder and Decoder model of JPEG. We will introduce the operation and fundamental theory of each block in the following sections.

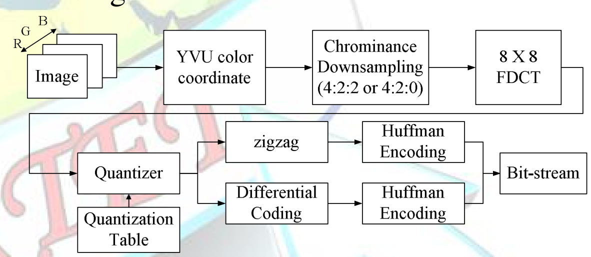

Fig 1.1.4(a) The Encoder model of JPEG compression standard

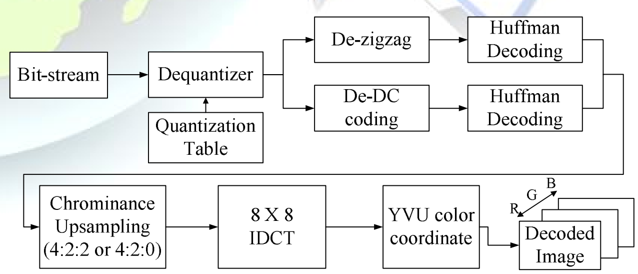

Fig 1.1.4(B) The Decoder model of JPEG compression standard

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1.1.5SHAPE-ADAPTIVE IMAGE COMPRESSION

Both the JPEG and JPEG 2000 image compression standard can achieve great compression ratio, however, both of them do not take advantage of the local characteristics of the given image effectively. Here is one new image compression algorithm proposed by Huang, it is called Shape Adaptive Image Compression, which is abbreviated as SAIC. Instead of taking the whole image as an object and utilizing transform coding, quantization, and entropy coding to encode this object, the SAIC algorithm segments the whole image into several objects, and each object has its own local characteristic and color. Because of the high correlation of the color values in each image segment, the SAIC can achieve better compression ratio and quality than conventional image compression algorithm. There are three parts of operation. First, the input image is segmented into boundary part and internal texture part. The boundary part contains the boundary information of the object, while the internal texture part contains the internal contents of the object such as color value. The two parts of the object is transformed and encoded, respectively.

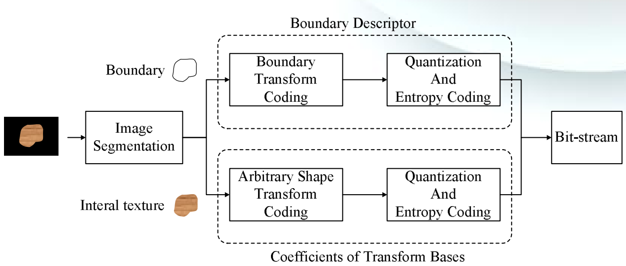

Fig 1.1.5The block diagram of shape-adaptive image compression

1.2 IMAGE RESTORATION

Image restoration is the operation of taking a corrupt/noisy image and estimating the clean, original reserving the process that blurred the image and such is performed by imaging a point source and use the point source image, which is called the point spread function to restore the image information lost to the blurring process. The objective of image restoration techniques is to reduce noise and recover resolution loss. Image processing techniques are performed either in the image domain or the frequency domain. The most straight forward and conventional technique for image restoration is deconvolution, which is performed in the frequency domain and after computing the fourier transform of both the image and the PSF and undo the resolution loss caused by the blurring factors. This deconvolution technique, because of its direct inversion of the PSF which typically has poor matrix condition number, amplifies noise and creates an imperfect deblurred image also conventionally the blurring process is assumed to be shift-variant. Hence more sophisticated techniques, such as regularized blurring, have been developed to offer robust recovery under different types of noises and blurring functions.

II RELEATED WORKS

TRADITIONAL GROUP BASED SPARSE REPRESENTATION

In the past several years image restoration has been widely studied. **Image restoration** can be stated as restoring the high quality image from the degraded low quality image. The main objective of our approach is to restore an image which is approximately similar to original image from a degraded

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image provide as the input. Here by using our approach we can deals with three image restoration problems that are, image inpainting, image deblurring, and image compressive sensing (CS) recovery. To restore the images from various types of degraded images such as from inpainted, blurred, compressive sensed image we need to perform some operations on original image and degraded image. Traditional patch based sparse representation provide inpainting algorithm through investigating the sparsity of the natural patches. Two novel concepts of sparsity at the patch level are proposed foe modeling the patch and patch reprensentation, which are two critical steps for patch propagation in the examplebased inpainting approach. First, patch structure sparsity is designed to measure the confidence of a patch located at the image structure (e.g., the edge or corner) by the sparseness of this nonzero similarities to the patches. The patch with larger structure sparsity will be designed higher priority for further inpainting. Second, it is assumed that the patch to field can be represented by the sparse linear combination of candidate patches under the local patch consistency constraint in a framework of sparse representation. Compared sparse representation forces the newly inpainted regions to be sharp and consistent with the surrounding structure.

TOTALVARIATION MINIMIZATION ALGORITHM

All vectors in feasible set have some chance to be chosen as the optimal point. By adding additional constraints related to the inherent properties of typical images, some irrelevant vectors are removed from the feasible set of the problem. This increases the chance of image-like vectors to be chosen as the optimal point and improves the performance of reconstruction.The sparsity of typical images in some specific domains, we elaborated on modifying **TV minimization algorithm** to improve the performance of reconstruction in compressive sensing method. Sparse expansions of image provided by DCT and contourlet transform were included as new constraints in the optimization problem of reconstruction algorithms. Simulation results showed that modified algorithms are superior to conventional TV minimization algorithm, and exploiting contourlet transform result in more improvement because of its ability to detect contours and special geometrical structures in image.

COSINE ALGORITHM

CoS is an iterative recovery algorithm that offers rigorous bounds on computational cost and storage. It is most suited for practical purposes due to the fact that it requires only matrix-vector multiplications with sampling matrix. For reconstruction, the most challenging part is to identify the locations of large values in the signal. To achieve this, CoS is iteratively invoked for that signal and at each iteration the current approximation induces a residual which has not been approximated as yet.

DISCRETE WAVELET TRANSFORM

Although the DCT-based image compression algorithms such as JPEG have provided satisfactory quality, it still leaves much to be desired. Thus, the new DWT-based image compression algorithms such as JPEG 2000 became increasingly popular. DWT (Discrete Wavelet Transform) is an application of subband coding; thus, before

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introducing DWT, we briefly describe the theory of subband coding. In subband coding, the spectrum of the input is decomposed into a set of bandlimitted components, which is called subbands. Ideally, the input signal will be filtered into lowpass and highpass components through analysis filters. After filtering, the data amount of the lowpass and highpass components will become twice that of the original signal; therefore, the lowpass and highpass components must be downsampled to reduce the data quantity. At the receiver, the received data must be upsampled to approximate the original signal. Finally, the upsampled signal passes the synthesis filters and is added to form the reconstructed approximation signal

METROPOLIS–HASTINGS ALGORITHM

Metropolis– Hastings algorithm is the workhorse of MCMC methods, both for its simplicity and its versatility, and hence the first solution to consider in intractable situations. The main motivation for using Markov chains is that they provide shortcuts in cases where generic sampling requires too much effort from the experimenter. Rather than aiming at the "big picture" immediately, as an accept-reject algorithm would do , Markov chains construct a progressive picture of the target distribution, proceeding by local exploration of the state space X until all the regions of interest have been uncovered. An analogy for the method is the case of a visitor to a museum forced by a general blackout to watch a painting with a small torch. Due to the narrow beam of the torch, the person cannot get a global view of the painting but can proceed along this painting until all parts have been seen.

III PROPOSED SCHEME AND METHODOLOGY

Group-based sparse representation (GSR modeling)

To rectify the problems of traditional patch-based sparse representation, a novel sparse representation modelling has been proposed in the unit of group instead of patch, aiming to exploit the local sparsity and the nonlocal self-similarity of natural images simultaneously in a unified framework. Each group is represented by the form of matrix, which is composed of nonlocal patches with similar structures. Thus, the proposed sparse representation modelling is named as group-based sparse representation (GSR). Moreover, an effective self-adaptive dictionary learning method for each group with low complexity is designed rather than dictionary learning from natural images, enabling the proposed GSR more efficient and effective.

Operations on original image: On original image we have to perform three main operations mentioned below to get the accurate results.

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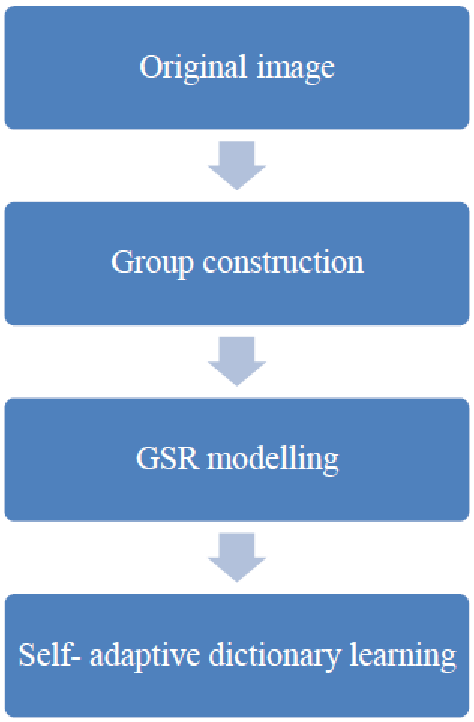
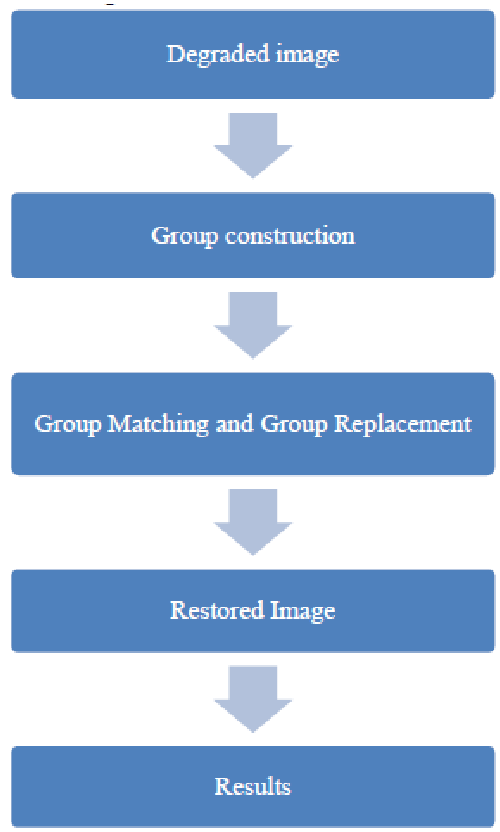


Operations on degraded image: Now for restoring the image which is approximately similar to original image from the degraded image we have to perform following operations on degraded image.



RESTORING THE IMAGE

Image x reconstruct from the degraded image y by using the following formula

$$y=Hx+n$$

where ,y are the stacked representations of original image and x are the stack representation of the degraded image, respectively, and n is the additive Gaussian white noise and H is a non-invertible linear degradation operator and it is represented in matrix form When H is a mask, the diagonal entries in image prior knowledge plays a critical role in image restoration algorithms, designing effective regularization terms to reflect the image priors is at the core of image restoration.

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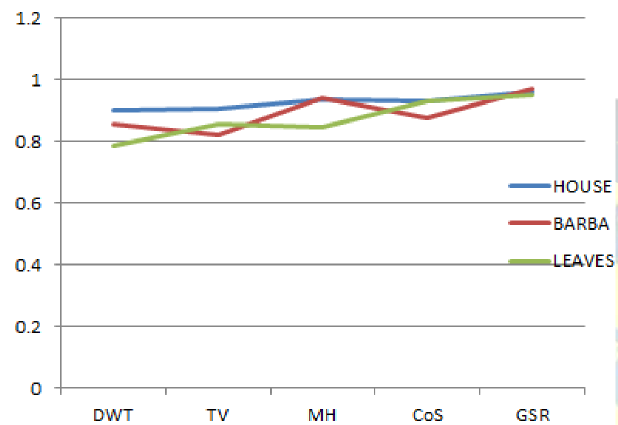
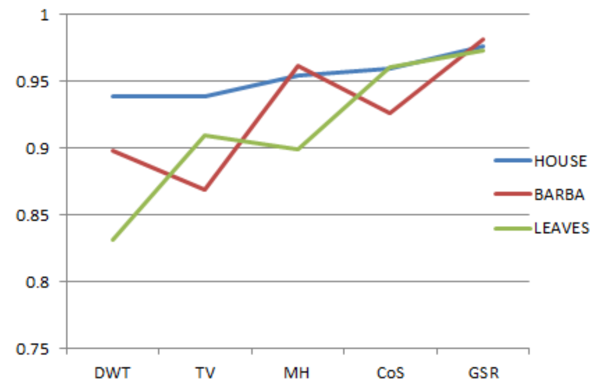
PERFORMANCE EVALUATION:

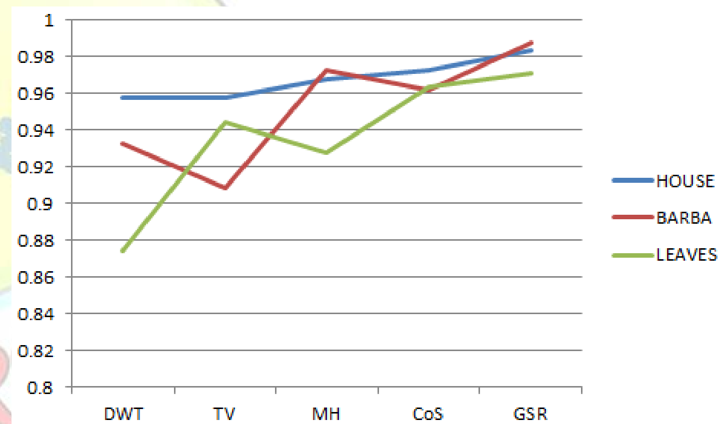
In this PSNR and FSIM are comparing with various CS recovery process. If the ratio increases, the value of PSNR and FSIM is also increasesIncreasing the value of PSNR and FSIM, the quality of the image increases.



PSNR value for 20% ratio



PSNR value for 30% ratio



PSNR value for 40%ratio

Table 1: PSNR and FSIM Comparisons with Various CS Recovery Methods (dB)

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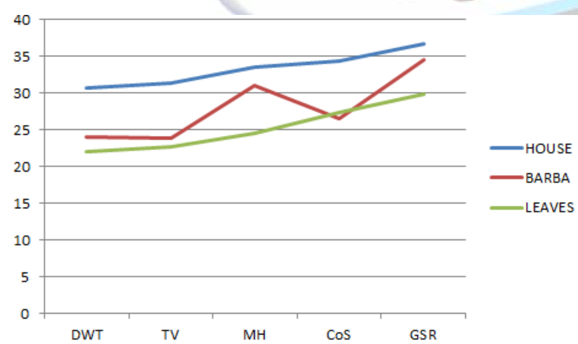
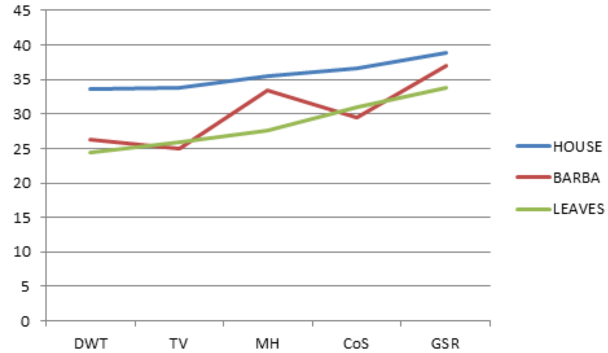
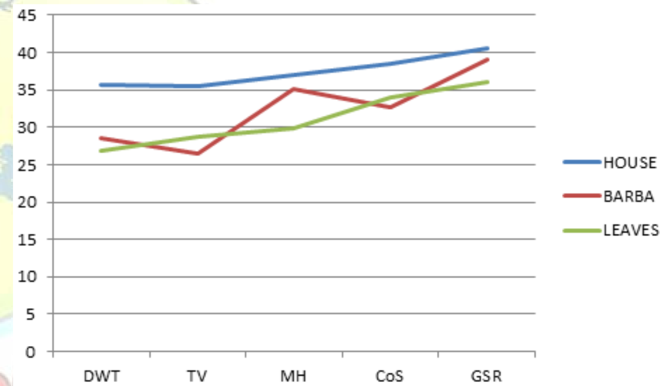
Ratio	Algorithms	House	Barbara	Leaves
20%	DWT	30.70/0.9029	23.96/0.8547	22.05/0.7840
	TV	31.44/0.9051	23.79/0.8199	22.66/0.8553
	MH	33.60/0.9370	31.09/0.9419	24.54/0.8474
	CoS	34.34/0.9326	26.60/0.8742	27.38/0.9304
	GSR	**36.78/0.9618**	**34.59/0.9703**	**29.90/0.9499**
30%	DWT	33.60/0.9391	26.26/0.8980	24.49/0.8314
	TV	33.75/0.9384	25.03/0.8689	25.85/0.9092
	MH	35.54/0.9546	33.47/0.9614	27.65/0.8993
	CoS	36.69/0.9592	29.49/0.9267	31.02/0.9606
	GSR	**38.93/0.9761**	**36.92/0.9811**	**33.82/0.9731**
40%	DWT	35.69/0.9576	28.53/0.9327	26.82/0.8741
	TV	35.56/0.9574	26.56/0.9088	28.79/0.9442
	MH	37.04/0.9676	35.20/0.9727	29.93/0.9276
	CoS	38.46/0.9724	32.76/0.9618	33.98/0.9637
	GSR	**40.60/0.9836**	**38.99/0.9877**	**36.07/0.9714**



FSIM value for 20% ratio



FSIM value for 30% ratio

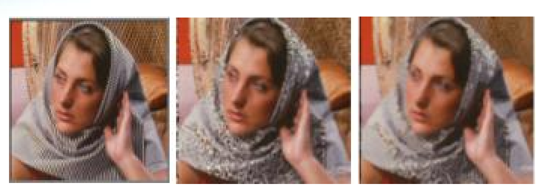


FSIM value for 40% ratio

IV. RESULT AND DISCUSSION

Image inpainting

Input DWT TV



MHCoS GSR

ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
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International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 4, Special Issue 3, February 2017

CONCLUSION

This approach for image restoration technique which uses group as the fundamental unit of sparse representation. Ignorance of the relationships between similar patches, such as self-similarity which is one of the problems associated with the previous patch-based sparse representation modelling is overcome by using this concept. Large scale optimization which is another problem associated with previous patch-based sparse representation modelling is also overcome by using a GSR-driven $\ell 0$-minimization approach which makes use of Split Bregman Iteration (SBI) algorithm. SBI algorithm makes GSR robust and tractable. Also our GSR is able to remove mixed Gaussian and impulse noise from the blurred images. On the whole, the GSR can make image restoration task easier by overcoming the problems associated with the previous approach. Further research work can include video restoration and other possible applications.

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