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WAVELET LIFTING SCHEME FOR IMAGE COMPRESSION BASED ON COMPRESSIVE SENSING

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Abstract- In **t**his paper proposes a joint framework where in lifting-based, separable, imagematched wavelets are estimated from compressively sensed images and are used forthe reconstruction of the same. Matched wavelet can be easily designed if full imageis available. Also compared to standard wavelets as sparsifying bases, matchedwavelet may provide better reconstruction results in compressive sensing (CS)application. Since in CS application, we have compressively sensed images instead offull images, and existing methods of designing matched wavelets cannot be used. Thus,we propose a joint framework that estimates matched wavelets from compressivelysensed images and also reconstructs full images. This project has three significantcontributions. First, lifting-based, image-matched separable wavelet is designed fromcompressively sensed images and is also used to reconstruct the same. Second, asimple sensing matrix is employed to sample data at sub-Nyquist rate such thatsensing and reconstruction time is reduced considerably. Third, a new multi-level L-Pyramid wavelet decomposition strategy is provided for separable waveletimplementation on images that leads to improved reconstruction performance.Compared toCS-based reconstruction using standard wavelets with Gaussian sensingmatrix and with existing wavelet decomposition strategy,the proposed methodologyprovides faster and better image reconstruction in compressive sensing application

Index Terms- Compressive Sensing, Lifting Theory, L-Pyramid and Wavelet transform

I. INTRODUCTION

Classical signal acquisition technique in the signal processing branch involves sensing the full signal at or above the Nyquist rate. In general, this signal is transformed to a domain where it is compressible. Only some of the largest coefficients of transformed signal having sufficient amount of energy are stored and transmitted to the receiver along with the position information of the transmitted Manuscript The Associate Editor coordinating the review process was Prof. Yue M. Lu. (Corresponding author: Naushad Ansari.) The transmitted signal is decoded at the receiver to recover the original signal. Thus, this process involves sensing the full signal, although most of the samples in the transformed domain are to be discarded. In [1] and [2], researchers proposed a compressed/ compressive sensing (CS) method that combines sensing and compression in one stage, where instead of sampling a signal sample-wise above Nyquist rate, signal projections are captured via a measurement basis. These samples are very few as compared to those sampled at Nyquist rate. If the signal is sparse in some transform domain and also if the measurement basis is incoherent with the sparsifying basis, then the full signal can be reconstructed with a good probability from a very few projections of the signal. In this context, wavelets are extensively used as a sparsifying basis in compressed sensing problems [2]. One of the advantages with wavelets is that there is no unique basis unlike Fourier transform. One may choose the set of basis depending upon

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the type of application. Since the wavelet basis are not unique, it is better to design wavelets that are matched to a given signal in a particular application. The designed wavelet basis are called signal-matched wavelets [3]–[5]. Motivated with the above discussion, this paper proposes to design matched wavelets for compressive sensing application. Unlike previous works on matched wavelets where wavelets are designed from fully sampled signal [3]–[9], this paper proposes a novel method of designing signal matched wavelets from compressively sensed images at the receiver. The proposed method employs a lifting based framework to design image-matched wavelets [10]. Many researchers have designed wavelets using lifting [5], [8], [11]–[17] that requires design of predict and update stage filters.

II. LITERATURE SURVEY

[1] Emmanuel J. In recent years, compressed sensing (CS) has attracted considerable attention in areas of applied mathematics, computer science, and electrical engineering by suggesting that it 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. [2] Anubha Gupta This paper proposes a new method of estimating both biorthogonalcompactly supported as well as semi-orthogonal infinitely/compactly supported waveletfrom a given signal. The method is based on maximizing projection of the given signalonto successive scaling subspace. This results in minimization of energy of signal in thewavelet subspace. The idea used to estimate analysis wavelet filter is similar to asharpening filter used in image enhancement.

[3] Anubha Gupta, Shiv Dutt Joshi This paper presents a new approach for theestimation of wavelets that is matched to a given signal in the statistical sense. Based onthis approach, a number of new methods to estimate statistically matched wavelets areproposed. The paper first proposes a new method for the estimation of statisticallymatched two band compactly supported biorthogonal wavelet system. Second, a newmethod is proposed to estimate statistically matched semiorthogonal two-band waveletsystem that results in compactly supported or infinitely supported wavelet. Next, theproposed method of estimating two-band wavelet system is generalized to -band waveletsystem.

[4] Naushad Ansari This paper proposes design of signal-matched wavelets via lifting.The design is modular owing to lifting framework wherein both predict and update stagepolynomials are obtained from the given signal. Successive predict stages are designedusing the least squares criterion, while the update stages are designed with total variationminimization on the wavelet approximation coefficients. Different design strategies for compression and denoising are presented. The efficacy of matched-wavelets is illustrated on transform coding gain and signal denoising.

[5] Joseph O Algorithms for designing a mother wavelet ( ) such that it matches a signal of interest and such that the family of wavelets 2 (2) (2) forms an orthonormal Riesz basis of 2( ) are developed. The algorithms are based on a closed form solution for finding the scaling function spectrum from the wavelet spectrum.

III. PROPOSED METHOD

We propose to use PCI sensing matrix that, to our understanding, is the simplestsensing matrix proposed so far and "actually" senses the image at sub-Nyquist rate bycapturing fewer pixels without sensing information about every pixel [32]. This isexplained as below.Consider an image X of dimension $m \times n$. Instead of sampling all the N(N = mn) pixelsof the image using the sensor array of the traditional camera, we capture M samples ofthe image using the proposed measurement matrix p, where M N. The measurementmatrix p has the entries shown below:

$$\Phi^{p}_{i,j} = \begin{cases} 1 & \text{if } i \in \{1,2,\ldots,M\} \text{ and } j \in \Omega \\ 0 & \text{otherwise,} \end{cases} \qquad (13)$$

Where,⊂{1,2,...,N}suchthat||=Mand|.|denotesthecardinalityof thetheset.

This sensing matrix is known as partial canonical identity (PCI) matrix because itconsistsofpartiallyselectedandpermutedrowsofthe identitymatrix.

Fig.1.1(a)Image(withdimension512×512)captured usingPCIsensingmatrixwith50% sampling ratio and with zeros filled at positions not sampled (b) Imagereconstructed from subsampled image using 'db4' wavelet

The PCI sensing matrix captures only M samples of the actual image; thus, actuallysub-samples the original image. This can be accomplished by using existing cameras byswitching ONonlyM sensorsofthesensorarray.Thisis unlikethe singlepixel camerawhere every captured pixel is the linear combination of the entire image pixel set. Also,in single pixel camera, one has to wait for M units of time to sense M number ofsamples, whereas all M samples are sensed in one unit of time in the case of PCIsensing matrix. Thus, the PCI sensing matrix reduces the sensing time by a factor of Mincomparisontoasinglepixelcamera.

Proposed L-Pyramid wavelet decomposition method for images

InthisSection,weproposeanewoptimizedstrategyofmulti-levelwaveletdecomposition on images. A separable wavelet transform is implemented on images byfirst applying 1-D wavelet transform along the columns and then along the rows of animage. This provides 1-level wavelet decomposition that consists of four componentslabeled as LL, LH, HL and HH, respectively. The same procedure is repeated on the LLpart of the wavelet transform k − 1-times to obtain k-level decomposition of an image(Fig.6a).WecallthisdecompositioasRegularPyramid(R-Pyramid)waveletdecomposition. Ingeneral,k-levelwaveletdecompositionofanimageconsistsofthefollowingcomponents:

LLk,LHi,HLiandHHi,wherei=1,2,...,k−1.

LHi,HLiandHHicomponentsareobtainedbyapplyingwavelettransformonthecolumnsandrowsofLLi−1component. LHiisobtainedbyfilteringLLi−1column-wise using a lowpass filter and filtering it row wise using a high pass filter. Thus, thecurrent nomenclature of labeling sub bands is: first character represents operation oncolumns and second character represents operation on rows, where operation implieshighpass or lowpass filtering denoted by symbols ‘H’ and ‘L’, respectively. In theconventional 2-D wavelet transform (Fig. 6a), wavelet decomposition is applied on LLipart only to obtain the (i + 1)th level coefficients. Since it is a separable transform,similar to 1-D wavelet transform wherein wavelet is applied repeatedly on lowpassfiltered branches, we propose to apply wavelet in the lowpass filtered directions ofLHi−1 and HLi−1 subbands in contrast to the conventional decomposition strategywhereinthesesubbandsareleftunaltered.

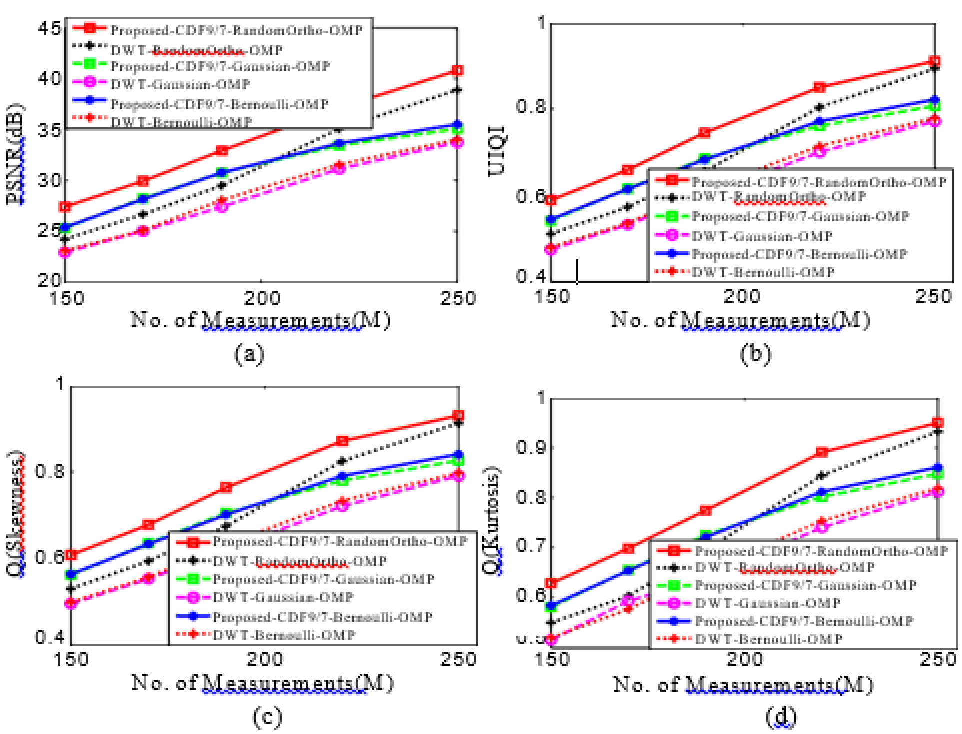
Thus, the proposed 2nd level wavelet decomposition is as shown in Fig. 6c. Since weapply wavelet in only one direction of LHi−1 and HLi−1 subbands, we notate thesesubbands differently compared to the conventional scheme. We assign subscript withboth ‘L’ and ‘H’ symbols of every subband to denote the no. of times wavelet has beenapplied in that direction. In order to understand this, let us first consider 1-level waveletdecomposition as shown in Fig. 6b that is similar to the conventional scheme shown inFig. 6a. However, the subbands are labeled as L1L1, L1H1, H1L1, and H1H1. In the2ndlevelwaveletdecomposition,waveletisappliedinbothdirectionsofL1L1subbandsleadingtoL2L2,L2H2,H2L 2,andH2H2subbands.

But in addition, wavelet is applied on the columns of L1H1 yielding two subbandsL2H1 and H2H1. Also, wavelet is applied on the rows of H1L1 subband yielding twosubbands H1L2 and H1H2. Applying similar strategy for the 3rd level decomposition,we obtain subbands as shown in Fig. 6d. We name this wavelet decomposition as L-shapedPyramid(L-Pyramid) waveletdecomposition.
The efficacy of the proposed L-Pyramid wavelet decomposition is shown in CS-basedimagereconstructionwithorthogonalDaubechieswavelet‘db4’andPCIsensingmatrix. Fig. 7 shows reconstruction accuracy in terms of PSNR (14) with samplingratios ranging from 10% to 90% averaged over 10 independent trials. We comparereconstruction accuracy at different sampling ratios with the existing RPyramid waveletdecomposition and with the proposed LPyramid wavelet decomposition on the samethree images: ‘Beads’, ‘Lena’ and ‘House’. From Fig.7, we note better results with L-Pyramid waveletdecompositioncomparedtoR-Pyramidwaveletdecomposition atsamplingratiosfrom90%to30%. Thereisconsiderablylessimprovementatlower samplingratiosof20%and10%(referto theenlargedviewinFig.7).Thismay beduetothereasonthat thenumberofsamples acquired at such lower sampling ratios do not contain enough information forgoodimagereconstruction.Inaddition,wenotethatperformanceisparticularly

improvedforimage‘House’thatisrichinlowfrequencies.Sincethelowpassbandsarerepeatedly broken in all the subbands in the proposed L-Pyramid unlike the R-Pyramid,images rich in lower frequenciesare benefited more. This, further,establishes thesignificanceofthe proposeddecompositionstrategy.

IV. EXPERIMENTAL RESULTS

In this section, we illustrate the reconstruction performance of compressed sensing image; we deploy both the OMP and Basis Pursuit on proposed sparse basis CDF9/7 wavelet transform (WT), DWT and DCT using Gaussian matrix, Bernoulli matrix and random orthogonal matrix measurements. To evaluate the performance of proposed algorithm we used open source databases [18]. The images are for 8-bit 256 × 256 pixels and 8-bit 64 × 64 pixels. We used different image quality indexes: PNSR, UIQI, Q(Skewness), Q(Kurtosis), SSIM, SSIM(Skewness), SSIM(Abs-Skewness), SSIM(Kurtosis) [19] [20] to evaluate the qualities of the compressed images. In order to make clearer comparisons, besides our proposed sparse basis CDF9/7 WT with three different measurements matrix's and Basis Pursuit (BP) algorithms or greedy optimization techniques as OMP and are also used. Wemadeexperimentson15imagesinour proposed image compression based on CS methods. Comparing the evaluation of imagequality (EIQ) indexes for the compressed image at several measurements M < N (N = 256), wenote that the higher measurements M, the better quality of image compression will be. Figures 3& 4 show the quality indexes of image compression obtained with proposed sparse CDF 9/7wavelettransform(WT)andsparseDWTwithOMPalgorithmperformedonthehumanbodyshown in Figure 2 . As example, in Figure 3 (a), the PSNR values of proposed sparse basis CDF9/7 with three measurements matrix and OMP in proposed framework is showing higher valuesthan sparse basis DWT with three measurements matrix and OMP in the range [150-250].Similarly, we also observes that other quality index values including new image quality indexesof proposed sparse basis CDF 9/7 WT are higher values than others. However, the new imagequality indexes also show higher value than original UIQI and SSIM. Comparing the evaluationof image quality (EIQ) indexes for the compressed image at several measurements M < N (N =256),we notethatthe higherthemeasurementsMgiventhebetterthe quality ofimagecompressionwillbe.Figures5&6alsoshowthequalityindexesofimagecompressionobtainedwith proposed sparse basis CDF9/7 WT and other techniques of sparse basis DWT or DCT withBPalgorithmwerealsousedontheBrain(MR)-1andBrain(MR)-2images.



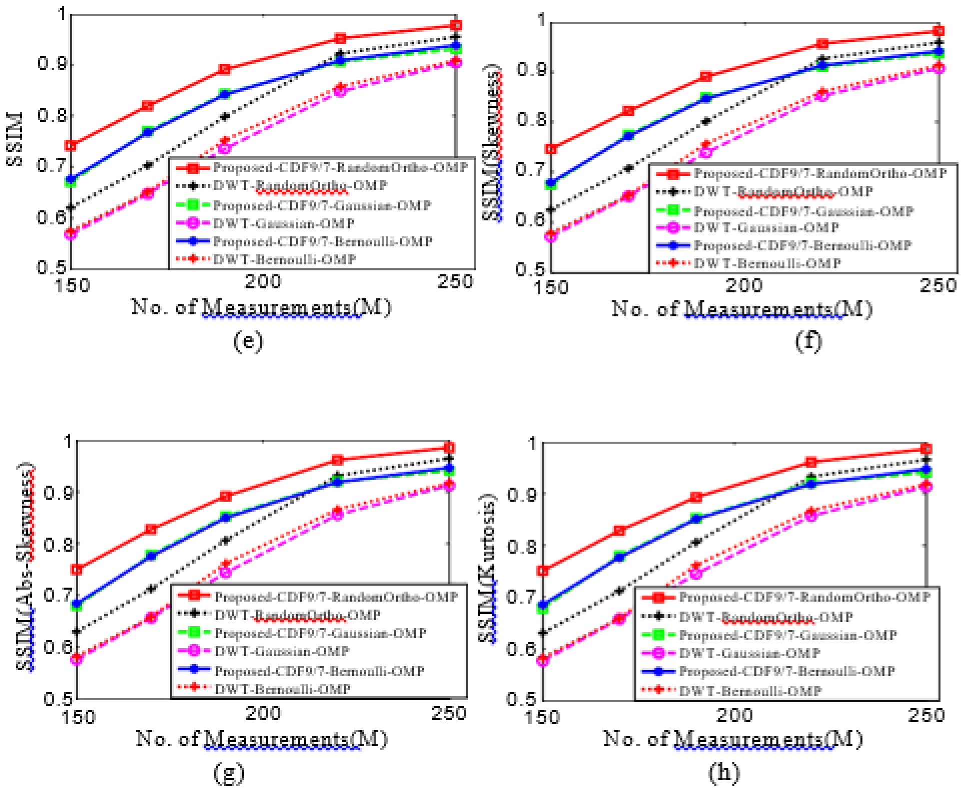


Figure 3: Plots of eight image quality indexes for human body muscle cells image versus number ofmeasurements (M)(M < N, N = 256)in the range [150-250] for proposed sparse basis CDF9/7 wavelettransformwiththreemeasurements matrixandOMPincludingthesparse basisDWT.

V. CONCLUSION

In this paper, we propose an image compression method based on compressive sensing with a wavelet lifting scheme framework that addresses the best-compressed image components and high-frequency feature preservation in medical images. The proposed method is also compared to three different matrices, namely Gaussian, Bernoulli, and random orthogonal measurement matrices, as well as image reconstruction using convex optimization techniques such as Basis Pursuit (BP) and greedy pursuit algorithms such as Orthogonal Matching Pursuit (OMP). Experiments show that the proposed sparse basis works. CDF9/7A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions. In the suggested framework with CS, wavelet transform compresses images better than sparse DWT or DCT with OMP or Basis Pursuit (BP) method.

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