

Image Reconstruction using Matched Wavelet for Partial Canonical Identity Matrix images

ASHOK VARDHAN CHINTA ¹, ARCHANA B.T ²

M.Tech Student, Department of Electronics and Communication Engineering, Dadi Institute of Engineering and Technology, Anakapalli, Jawaharlal Nehru Technological University Kakinada ¹

Sr.Assistant Professor, Department of Electronics and Communication Engineering, Dadi Institute of Engineering and Technology, Anakapalli, Jawaharlal Nehru Technological University Kakinada ²

Abstract: *This method proposes a joint framework wherein lifting-based, separable, image-matched wavelets are estimated from compressively sensed images and are used for the reconstruction of the same. Matched wavelet can be easily designed if full image is available. Also compared to standard wavelets as scarifying bases, matched wavelet may provide better reconstruction results in compressive sensing (CS) application. Since in CS application, we have compressively sensed images instead of full images, existing methods of designing matched wavelets cannot be used. Thus, we propose a joint framework that estimates matched wavelets from compressively sensed images and also reconstructs full images. This method has three significant contributions. First, lifting-based, image-matched separable wavelet is designed from compressively sensed images and is also used to reconstruct the same.*

Second, a simple sensing matrix is employed to sample data at sub-Nyquist rate such that sensing and reconstruction time is reduced considerably. Third, a new multi-level L-Pyramid wavelet decomposition strategy is provided for separable wavelet implementation on images that leads to improved reconstruction performance. Compared to CS-based reconstruction using standard wavelets with Gaussian sensing matrix and with existing wavelet decomposition strategy, the proposed methodology provides faster and better image reconstruction in compressive sensing application.

Keywords:

1. INTRODUCTION

Image processing is processing of images using mathematical operations by using any form of signal processing for which the input is an image, a series of images, or a video, such as a photographer video frame; the output of image processing may be either an image or a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a dimensional signal and applying standard signal-processing techniques to it. Images are also processed as three-dimensional signals where the third-dimension being time or the z-axis. Image processing usually refers to digital image processing, but optical and analog image processing also are possible [1]. This article is about general techniques that apply to all of them. The acquisition of images (producing the input image in the first place) is referred to as imaging. Closely related to image processing are computer graphics and computer vision. In computer graphics, images are manually made from physical models of objects, environments, and lighting, instead of being acquired (via imaging devices such as cameras) from natural scenes, as in most animated movies. Computer vision, on the other hand, is often considered high-level image processing out of which a machine/computer/software intends to decipher the physical contents of an image or a sequence of images (e.g., videos or 3D full-body magnetic resonance scans).

In modern sciences and technologies, images also gain much broader scopes due to the ever growing importance of scientific visualization (of often large-scale complex scientific/experimental data). Examples include microarray data in genetic research, or real-time multi-asset portfolio trading in finance. Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph

and output may be image or characteristics associated with that image. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them [2].

It is among rapidly growing technologies today, with its applications in various aspects of a business. Image Processing forms core research area within engineering and computer science disciplines too. Image processing basically includes the following three steps.

- Importing the image with optical scanner or by digital photography.
- Analyzing and manipulating the image which includes data compression and image enhancement and spotting patterns that are not to human eyes like satellite photographs.
- Output is the last stage in which result can be altered image or report that is based on image analysis.

2. BACKGROUND

Literature Survey

Joint framework for signal reconstruction using matched wavelet estimated from compressively sensed data: In compressive sensing (CS), signal $x \ N \times 1$ is recovered from its fewer measured samples $y \ M \times 1$ in noise free case using optimization framework, where $A \ M \times N$ is the measurement matrix and $N > M$. Here, the original signal x is known to be sparse in some domain, say the wavelet domain W . Any wavelet can be used as the sparsifying basis, but wavelet matched to a given signal should yield better reconstruction results compared to any existing wavelet because it is supposed to provide best representation of a given signal. So far, no method exists in literature for the estimation of matched wavelet from compressively sensed data that can also be utilized at the same time for the efficient signal reconstruction of a compressively sensed signal. In this work, we address this problem.

An introduction to compressive sensing: Conventional approaches to sampling signals or images follow Shannon's theorem: the sampling rate must be at least twice the maximum frequency present in the signal (Nyquist rate). In the field of data conversion, standard analog-to-digital converter (ADC) technology implements the usual quantized Shannon representation - the signal is uniformly sampled at or above the Nyquist rate. This article surveys the theory of compressive sampling, also known as compressed sensing or CS, a novel sensing/sampling paradigm that goes against the common wisdom in data acquisition. CS theory asserts that one can recover certain signals and images from far fewer samples or measurements than traditional methods use.

Compressive sensing and structured random matrices: These notes give a mathematical introduction to compressive sensing focusing on recovery using ℓ_1 -minimization and structured random matrices. An emphasis is put on techniques for proving probabilistic estimates for condition numbers of structured random matrices. Estimates of this type are key to providing conditions that ensure exact or approximate recovery of sparse vectors using ℓ_1 -minimization.

Restricted isometrics for partial random circulant matrices: In the theory of compressed sensing, restricted isometric analysis has become a standard tool for studying how efficiently a measurement matrix acquires information about sparse and compressible signals. Many recovery algorithms are known to succeed when the restricted isometry constants of the sampling matrix are small. Many potential applications of compressed sensing involve a data-acquisition process that proceeds by convolution with a random pulse followed by (nonrandom) sub sampling. At present, the theoretical analysis of this measurement technique is lacking. This paper demonstrates that the s th order restricted isometry constant is small when the number m of samples satisfies $m \geq (s \log n)^{3/2}$, where n is the length of the pulse. This bound improves on previous estimates, which exhibit quadratic scaling [3].

Compressed imaging with a separable sensing operator: Compressive imaging (CI) is a natural branch of compressed sensing (CS). Although a number of CI implementations have started to appear, the design of

efficient CI system still remains a challenging problem. One of the main difficulties in implementing CI is that it involves huge amounts of data, which has far-reaching implications for the complexity of the optical design, calibration, data storage and computational burden. In this paper, we solve these problems by using a two-dimensional separable sensing operator. By so doing, we reduce the complexity by factor of 106 for megapixel images. We show that applying this method requires only a reasonable amount of additional samples.

The simplest measurement matrix for compressed sensing of natural images: There exist two main problems in currently existing measurement matrices for compressed sensing of natural images, the difficulty of hardware implementation and low sensing efficiency. In this paper, we present a novel simple and efficient measurement matrix, Binary Permuted Block Diagonal (BPBD) matrix. The BPBD matrix is binary and highly sparse (all but one or several “1”s in each column are “0”s). Therefore, it can simplify the compressed sensing procedure dramatically. The proposed measurement matrix has the following advantages, which cannot be entirely satisfied by existing measurement matrices. (1) It has easy hardware implementation because of the binary elements; (2) It has high sensing efficiency because of the highly sparse structure; (3) It is incoherent with different popular sparsity basis' like wavelet basis and gradient basis; (4) It provides fast and nearly optimal reconstructions. Moreover, the simulation results demonstrate the advantages of the proposed measurement matrix.

Adaptive 2-d wavelet transform based on the lifting scheme with preserved vanishing moments: In this method, we propose novel adaptive wavelet filter bank structures based on the lifting scheme. The filter banks are non-separable, based on quincunx sampling, with their properties being pixel-wise adapted according to the local image features. Despite being adaptive, the filter banks retain a desirable number of primal and dual vanishing moments. The adaptation is introduced in the predict stage of the filter bank with an adaptation region chosen independently for each pixel, based on the intersection of confidence intervals (ICI) rule. The image denoising results are presented for both synthetic and real-world images. It is shown that the obtained wavelet decompositions perform well, especially for synthetic images that contain periodic patterns, for which the proposed method outperforms the state of the art in image denoising.

3. EXISTING SYSTEMS

In existing system, we used to design signal-matched wavelets using lifting wherein both predict and update stage polynomials are obtained from a given signal. Successive predict stages are designed using the least squares criterion, while the update stages are designed with total variation minimization on the wavelet approximation coefficients. We use two design methods. Method-1 designs signal matched filters with no constraint of linear phase property imposed on filters, while method-2 designs linear phase scaling and wavelet filters [4]. We test our design methods on some randomly picked speech and music clips and compare results of designed wavelets with standard wavelets on transform coding gain and signal denoising. The signal-matched wavelets are designed differently for compression (illustrated via transform coding gain) and denoising. The work proposed in this paper is carried out independently, although it is noticed to have some similarity in the design approach. This work differs from in the following ways.

- In this work, we design signal-matched wavelets for 1- D signals with 2-tap update and the predict polynomials in the powers of z and z^{-1} , respectively. This leads to the design of signal-matched $5/3$ and $9/7$ wavelets with one and two stages of predict-update pairs, respectively. Other variations on number of filter taps or different polynomials in z or z^{-1} will not lead to these wavelets. On the other hand, designs nonseparable wavelets for images without any such focus.
- We show that signal-matched wavelets designed differently in different applications lead to better designs. Here, a different approach is proposed to design matched wavelet for denoising compared to compression.
- Also, we use total variation minimization constraint in the update stage, while uses a constraint related to the non separable quincunx lattice of the image.

THEORY OF LIFTING

Lifting, also known as second generation wavelets, is a technique for either factoring existing wavelet filters into a finite sequence of smaller filtering steps or constructing new customized wavelet basis. A general lifting scheme consists of three steps: Split, Predict, and Update.

Split: In the split step, given input signal is split into two disjoint sets, generally even indexed and odd indexed samples, labeled as $x_e[n]$ and $x_o[n]$, respectively. The original signal can be recovered perfectly by interlacing or combining this even and odd indexed sample stream. The corresponding filter bank structure is also called as the Lazy wavelet system and the related filter bank structure.

Predict or Dual Lifting Step: In the predict stage, one of these two disjoint sets is predicted from the other set. For example, we predict even samples from the neighboring odd samples by using the predictor $P \equiv T(z)$. Predict stage is equivalent to applying a high-pass filter on the input signal.

Update or Primal Lifting Step: This step modifies the analysis lowpass filter and provides the coarse approximation of the signal. The update step is denoted with the symbol $U \equiv S(z)$. This is also called as the primal lifting step or simply, the lifting step [5].

4. RELATED WORK

Purpose of Image processing

The purpose of image processing is divided into 5 groups. They are:

- a) Visualization - Observe the objects that are not visible.
- b) Image sharpening and restoration - To create a better image.
- c) Image retrieval - Seek for the image of interest.
- d) Measurement of pattern – Measures various objects in an image.
- e) Image Recognition – Distinguish the objects in an image.

Image Processing is a technique to improve raw images received from cameras or sensors placed on satellites, space probes and aircrafts or pictures taken in normal life for various applications. Various techniques have been developed in Image Processing during the last five decades. Most of the techniques are developed for enhancing images obtained from unmanned spacecrafts, space probes and military inspection flights [6]. Image Processing systems are becoming popular due to easy availability of powerful personnel computers, large size memory devices, graphics software. Image Processing is used in various applications such as Remote Sensing, Medical Imaging, Textiles, Material Science, Military, Film industry, Document processing , Graphic arts The common steps in image processing are image scanning, storing, enhancing and interpretation. Image processing is a technique in which we enhance the data (raw images) sensed from the sensors placed on different artifacts of the life for various specified applications. The result is of greater quality as the objects are clearly visible as compared to the original sensed image. There are various fundamental steps involved in the image processing that is representation of images, preprocessing of images, enhancement, restoration, analysis, reconstruction of images and image data compression [7].

An image is an array, or a matrix, of square pixels (picture elements) arranged in columns and rows. In a (8-bit) grey scale 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.

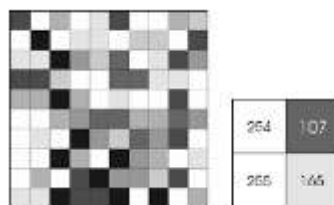


Figure .1: Image

Fundamental steps in Image processing

1. Image acquisition: to acquire a digital image
2. Image pre-processing: to improve the image in ways that increases the chances for success of the other processes.
3. Image segmentation: to partitions an input image into its constituent parts or objects.
4. Image representation: to convert the input data to a form suitable for computer processing.
5. Image description: to extract features that result in some quantitative information of interest or features that are basic for differentiating one class of objects from another.
6. Image recognition: to assign a label to an object based on the information provided by its descriptors.
7. Image interpretation: to assign meaning to an ensemble of recognized objects.

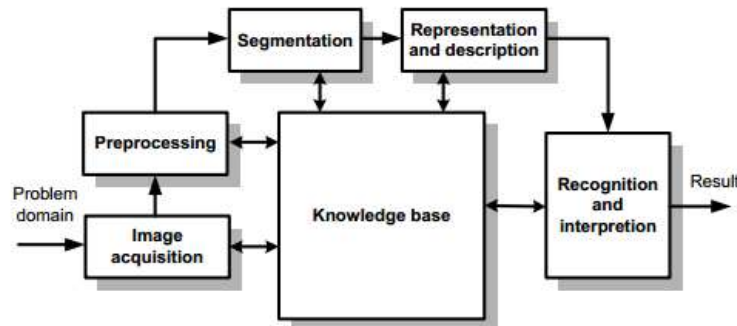


Figure.2: Architecture

5. PROPOSED SYSTEM

All the methods discussed above design signal-matched wavelet using the full signal at the input. So far, to the best of our knowledge, no method has been proposed that designs signal or image-matched wavelets from compressive or partial measurements. This method addresses this problem from the point of view of image reconstruction [8]. Below are the salient contributions of this method:

- 1) We propose design of an image-matched separable wavelet in the lifting framework from a compressively sensed image, that is also used to reconstruct the image.
- 2) In general, Gaussian or Bernoulli measurement matrices are used in compressive sensing application. We propose to use partial canonical identity matrix (PCIM) to sample data at the sub-Nyquist rate such that sensing time is reduced considerably.
- 3) For the separable 2D wavelet transform, a new multilevel wavelet decomposition strategy is proposed that leads to improved reconstruction performance. We name this new wavelet decomposition strategy as multi-level L-Pyramid wavelet decomposition.

In general, 3-level wavelet decomposition is used as a norm in all wavelet based applications including compressive sensing. Hence, we have used 3-level wavelet decomposition throughout this work.

L-Pyramid wavelet decomposition method for images: We propose a new optimized strategy of multi-level wavelet decomposition on images. A separable wavelet transform is implemented on images by first applying 1-D wavelet transform along the columns and then along the rows of an image. This provides 1-level wavelet decomposition that consists of four components labeled as LL, LH, HL and HH, respectively. The same procedure is repeated on the LL part of the wavelet transform k-times to obtain k-level decomposition of an image. We call this decomposition as Regular Pyramid (R-Pyramid) wavelet decomposition.

Method of designing matched wavelet from compressively sensed images: We propose a joint framework for signal reconstruction in CS wherein we are estimating wavelet from the compressively sensed image and use it for efficient image reconstruction at the same time. Since the proposed work is on separable wavelets, we require to estimate matched wavelet for row and column directions separately. Thus, before proceeding with the matched wavelet design, we present the scanning mechanism of rows and columns data in images as used in this work [9].

Scanning Mechanism for Row- and Column-wise Data: As stated earlier, we require to estimate matched wavelet for both the row and column directions. One easier method can be designing matched wavelet on row- or column-vectorized image and use the same wavelet, later, along both the columns and rows as a separable wavelet. Instead, we propose to design matched wavelet separately for the row- and column-directions using the following two scanning patterns:

Raster scanning pattern: The image is scanned according to the scanning pattern, wherein rows or columns are stacked one after the other to obtain 1-D signal for both the directions. However, this will cause discontinuity in the 1-D signal at the transitions when one column ends and another starts and likewise, for the rows.

Serpentine scanning pattern: In order to avoid this discontinuity, an alternate way is to scan all even rows or columns in the reverse direction

Methodology of Matched Wavelet Design: The proposed methodology has three stage. In stage-1, we obtain coarse image estimate from compressively (partially) sensed samples using a standard wavelet. We call this a coarser estimate because the wavelet used is not matched to the given signal and hence, the original signal may not be that sparse over this wavelet compared to that with the matched wavelet. This will impact the reconstruction performance. In stage-2, we estimate matched analysis wavelet filter that provides sparser subband wavelet (detail) coefficients than those obtained from the standard wavelet in stage-1. Using these estimated filters and the coarser signal estimate of stage-1, we design all filters of the matched wavelet system. In stage- 3, we reconstruct signal from measured sub-samples using the matched wavelet estimated in stage-2 [5].

In the application of CS-based image reconstruction, the proposed methodology of this paper has three contributions:

- **Proposed use of PCI sensing matrix:** that is computationally inexpensive compared to the existing Gaussian matrix, but provides approx. 2-5 dB lower performance compared to the existing Gaussian matrix.
- **Proposed L-Pyramid wavelet decomposition:** that provides better results in CS-based image reconstruction compared to the existing R-Pyramid wavelet decomposition.
- **Design of image-matched wavelets:** wherein a wavelet is designed from a compressively sensed image and is used for the reconstruction of the same. Hence, an image is recovered by employing a wavelet matched to it.

Reconstruction methods in image processing: Image reconstruction techniques are used to create 2-D and 3-D images from sets of 1-D projections. These reconstruction techniques form the basis for common imaging modalities such as CT, MRI, and PET, and they are useful in medicine, biology, earth science, archaeology, materials science, and nondestructive testing. The mathematical foundation for these reconstruction methods are the Radon transform, the inverse Radon transform, and the projection slice theorem. Computational techniques include filtered back projection and a variety of iterative methods. Several projection geometries are commonly used, including parallel beam, fan beam, and cone beam. The Shepp-Logan phantom image is often used to evaluate different reconstruction algorithms [8].

Compressed sensing: Compressive sensing has emerged as an area that opens new perspectives in signal acquisition and processing. It appears as an alternative to the traditional sampling theory, endeavoring to reduce the required number of samples for successful signal reconstruction [10]. In practice, compressive sensing aims to provide saving in sensing resources, transmission, and storage capacities and to facilitate signal processing in the circumstances when certain data are unavailable. To that end, compressive sensing relies on the mathematical algorithms solving the problem of data reconstruction from a greatly reduced number of measurements by exploring the properties of sparsity and incoherence. Compressed sensing (also known as compressive sensing, compressive sampling, or sparse sampling) is a signal processing technique for efficiently acquiring and reconstructing a signal, by finding solutions to underdetermined linear systems. This is based on the principle that, through optimization, the sparsity of a signal can be exploited to recover it from far fewer samples than required by the Nyquist–Shannon sampling theorem. There are two conditions under which recovery is possible [9]. The first one is sparsity, which requires the signal to be sparse in some domain. The second one is incoherence, which is applied through the isometric property, which is sufficient for sparse signals.

6. RESULTS



Figure. 3: Reconstructed with db4 wavelet and Reconstructed with matched wavelet

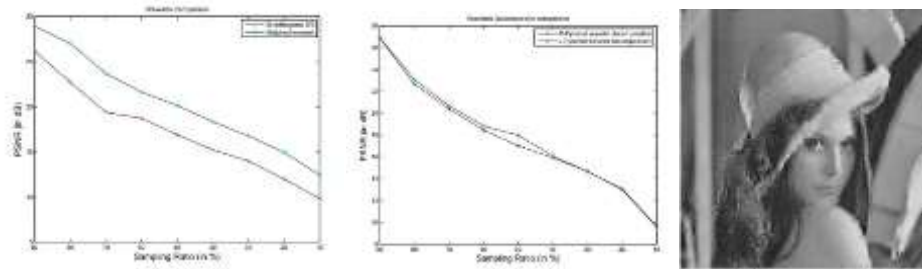
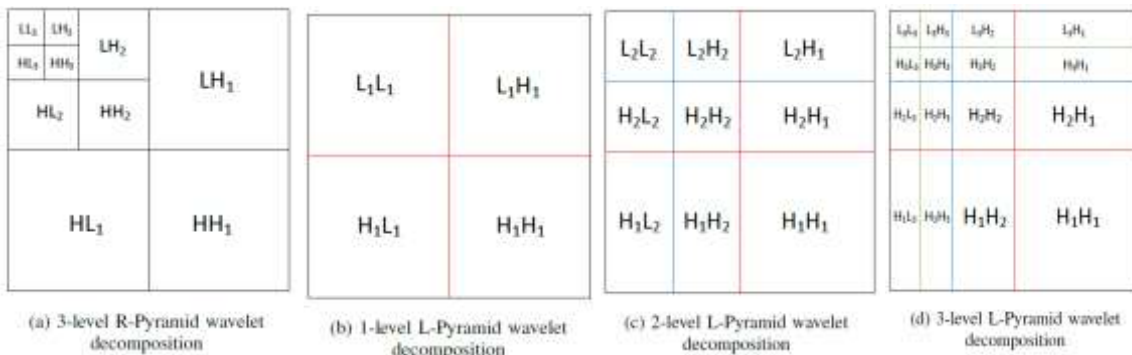


Figure.4: Pci matrix sensing Bi orthogonal 5/3 wavelet decomposition



7. CONCLUSION

In this method, we have proposed a joint framework wherein image-matched wavelets have been designed from compressively sensed images and later, used for reconstruction or recovery of the full image. We have also proposed to use a partial canonical identity sensing matrix for CS-based reconstruction of images that performs much faster compared to the existing Gaussian or Bernoulli matrices and hence, is suited for time-bound real-time reconstruction based applications. Although there is a slight degradation in performance with the proposed sensing matrix but that is easily covered up by the matched wavelet design. We have also provided a new multi-level L-Pyramid wavelet decomposition strategy that works much more efficiently compared to the standard wavelet decomposition method. Overall, the proposed work with different sensing matrix, new wavelet decomposition strategy, and image-matched wavelets provide much better reconstruction results with ease of hardware implementation in CS-based image reconstruction compared to the existing methodology.

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Author's Profiles:

ASHOK VARDHAN CHINTA is M.Tech Student, Department of Electronics and Communication Engineering in Dadi Institute of Engineering & Technology (DIET) - Anakapalli, affiliated with Jawaharlal Nehru Technological University-Kakinada, Andhra Pradesh, India. He is completed B.Tech from Swarnandhra Institute of Engineering and Technology, Narsapur, JNTU Kakinada. He is Pursuing M-Tech (systems and signal processing) from DIET. He is well known Skills on Basic Programming in C Language, Microsoft Office, Excel, Windows XP/7 Operating systems.

ARCHANA B.T working with as Assistant Professor, Department of Electronics and communication Engineering, Dadi Institute of Engineering & Technology (DIET) - Anakapalli, affiliated with Jawaharlal Nehru Technological University-Kakinada. She is completed B.Tech (ECE) and M.Tech (Systems and Signal Processing) from Kerala University Kakinada. She is completed in Master Degree in ECE from Jawaharlal Nehru Technological University, India. She has 5 + years good teaching experience with taught various subjects on good knowledge on EDC, SS, ECA, EMWTL, AC, DC, STLD, VLSI and along with ECE subjects. She published research 3 papers in reputed International and national level conferences\Journals\Magazines. She attended 4 workshops. She is Participated and active member in academic, curriculum and administrative works in various organizations.