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Low Latency Corrective Feedback Algorithm for Binary Compressed Sensing

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ABSTRACT: Compressed sensing takes advantage of the redundancy in many interesting signals . Compressed sensing typically starts with taking a weighted linear combination of samples also called compressive measurements in a basis different from the basis in which the signal is known to be sparse. In the existing system, low density parity check codes are used for the process of predicting the compressed sensing scheme through metric matching. The proposed architectures offer high frequency of operation and low reconstruction time when compared to the state-of-the-art designs. Specifically, the 65-nm ASIC realization operates at a maximum frequency of 500 and 666.67 MHz and offer a reconstruction time of 6.3 and 4.7 ns, respectively, for a 64 × 256 deterministic measurement matrix. In the proposed system, design of low latency corrective feedback algorithm (LLCF) is developed. The algorithm is focused on correcting the binary dead codes and utilizes it to self-repair through a corrective iteration process. The system, performs better compared to the existing interval passing algorithm in terms of latency. These codes are encrypted through LDPC encoder. The proposed system is simulated in MODELSIM and implemented in XILINX ISE.

KEYWORDS: Compressed sensing, low density parity check ,interval passing algorithm, modelsim ,Xilinx ISE

I.INTRODUCTION

Compressed sensing (CS) has drawn considerable attention in recent years. Introduced by Donoho, it is a technique for reconstructing sparse signals from a small set of measurements. Let x ∈ RN be a K-sparse signal with at most K nonzero entries, K, N. Let A ∈ RM×N be a measurement matrix which maps x into a smaller measurement vector y ∈ RM as given by the following equation: y = Ax. One method of

recovering x from y is to find x with the smallest l0- norm, which is a NP-hard technique. Another method is to find x with the smallest l1-norm. The l1- norm minimization based on linear programming (LP) for CS, called basis pursuit (BP), has an excellent performance in the recovery of the sparse signals. The high complexity of BP makes it impractical when the matrix dimension is large. There exist relatively less complex greedy algorithms such as orthogonal matching pursuit (OMP), CoSaMP, iterative hard thresholding (IHT) which iteratively compute an approximation to the original signal. Several hardware realizations of OMP have been reported in the literature, which exhibit trade off between complexity and accuracy.

[1] Suppose x is an unknown vector in Ropf ^{m} (a digital image or signal); we plan to measure n general linear functionals of x and then reconstruct. If x is known to be compressible by transform coding with a known transform, and we reconstruct via the nonlinear procedure defined here, the number of measurements n can be dramatically smaller than the size m. Thus, certain natural classes of images with m pixels need only n=O(m $^{1/4}$ log $^{5/2}$ (m)) nonadaptive nonpixel samples for faithful recovery, as opposed to the usual m pixel samples. More specifically, suppose x has a sparse representation in some orthonormal basis (e.g., wavelet, Fourier) or tight frame (e.g., curvelet, Gabor)-so the coefficients belong to an lscr $_{p}$ ball for 02 error O(N $^{1/2-1}$ p/). It is possible to design n=O(Nlog(m)) nonadaptive measurements allowing reconstruction with accuracy comparable to that attainable with direct knowledge of the N most important coefficients. Moreover, a good approximation to those N important coefficients is extracted from the n measurements by solving a linear program-Basis Pursuit in signal processing.

The nonadaptive measurements have the character of "random" linear combinations of basis/frame elements. Our results use the notions of optimal recovery, of n-widths, and information-based complexity. We estimate the Gel'fand n-widths of lscr $_{p}$ balls in high-dimensional Euclidean space in the case 0

[2]A low-density parity-check code is a code specified by a parity-check matrix with the

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following properties: each column contains a small fixed number j \geq 3 of l's and each row contains a small fixed number k > j of l's. The typical minimum distance of these codes increases linearly with block length for a fixed rate and fixed j . When used with maximum likelihood decoding on a sufficiently quiet binary-input symmetric channel, the typical probability of decoding error decreases exponentially with block length for a fixed rate and fixed j . A simple but nonoptimum decoding scheme operating directly from the channel a posteriori probilities is described. Both the equipment complexity and the data-handling capacity in bits per second of this decoder increase approximately linearly with block length. For j > 3 and a sufficiently low rate, the probability of error using this decoder on a binary symmetric channel is shown to decrease at least exponentially with a root of the block length. Some experimental results show that the actual probability of decoding error is much smaller than this theoretical bound.

[3]The Interval-Passing Algorithm (IPA) is used to reconstruct non-negative real signals using binary measurement matrices in compressed sensing (CS). The failures of the algorithm on stopping sets, also non-decodable configurations in iterative decoding of LDPC codes over the binary erasure channel (BEC), shows a connection between iterative reconstruction algorithm in CS and iterative decoding of LDPC codes over the BEC. In this paper, a stopping-set based approach is used to analyze the recovery of the IPA. We show that a smallest stopping set is not necessarily a smallest configuration on which the IPA fails and provide sufficient conditions under which the IPA recovers a sparse signal whose non-zero values lie on a subset of a stopping set. Reconstruction performance of the IPA using IEEE 802.16e LDPC measurement matrices are provided to show the effect of the stopping sets in the performance of the IPA.

[4] Software reliability is highly affected by software quality attributes and measurements. Faults, bugs, and errors are shown not only in the development process but also in end-user period hereby it is required to detect these issues earlier. These are detected by software quality and object oriented metrics which are commonly used in the

fault detection process. CK, MOOD and QMOOD metrics are the most common metrics applied in this area. In this paper is to aim to provide information about popular software quality metrics and their usage in terms of software fault prediction studies. For this purpose, in this work, these three metrics were analysed separately and their acquisition

II.CPLD KIT

The hardware unit consists of XILINX XC9572XL based CPLD trainer kit. The board contains the 1600 gates, 72 macro cells, 100 Pin XC9572XL CPLD with 72 user I/O's. An on-board power supply includes 3.3V regulator, which regulates Vcc internal & Vcc I/O for the CPLD.

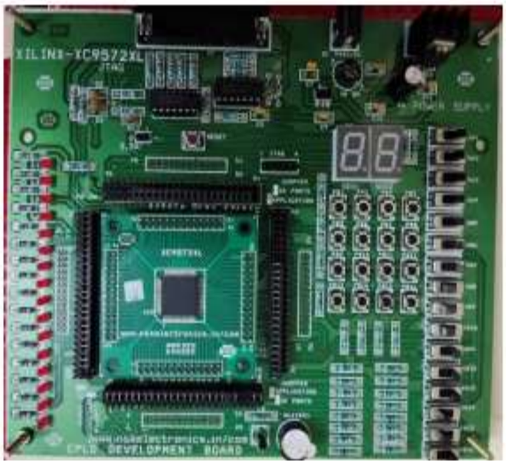

Figure 2.1 CPLD KIT

A 40 MHz crystal oscillator provides clock source that is directly connected to GCK1 clock input on the 9572XL. All user I/O pins are brought out of the 9572XL device. Peripheral interfaces like LEDs, 7 segment displays, key switches and buzzer are provided on board. Separate jumper settings have been provided for accessing the I/Os for other external applications. A built-in JTAG programmer board is also available for programming the XC9572XL.

The XILINX-XC9573XL is a 3.3V targeted for high performance, low voltage applications in the leading- edge communications and computing systems.It comprises of four 54V18 Function Blocks, providing 1,600 usable gates with propagation delays of 5 ns. The FPGA processor processes the code dumped in it through the JTAG port and results in the glowing of the LED according to the input sequence.

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Figure 2.2 XILINX-XC9573XL

III.METHODOLOGY:

The algorithm focuses on correcting the binary dead codes and utilizes it to self-repair through a corrective iteration process. The system performs better comparing to the existing interval passing algorithm in terms of latency. These codes are encrypted through LDPC encoder. The proposed system is simulated in MODELSIM and implemented in XILINX ISE.

BLOCK DIAGRAM:

The input data sequence is provided and the corrective feedback mechanism corrects the incoming signals and based on the sparsity of the signal, only a portion of the signal is concentrated. The signal is encoded using the Low Density Parity Check mechanism and sent for compressed sensing. After the signal is compressed, and the performance measurement of the signal is measured using get metrics. Then finally, the noise is removed from the signal

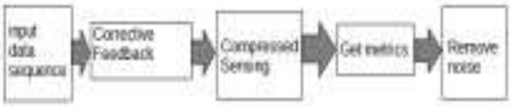

Figure 3.1 PROPOSED BLOCK DIAGRAM

INPUT DATA SEQUENCE:

Let x=[x1 ,x2,…..xn] be a k-sparse signal with k non zero entries k<<N. In BCS, each entry xi of vector x is binary valued, that is xi belongs to {0,1}. The sparsity of the given signals are checked. For each sparsity atleast 100 random signals are generated and 50 reconstruction iterations takes place.

CORRECTIVE FEEDBACK:

The algorithm used in the proposed technique is low latency corrective feedback (LLCF) algorithm. Here the latency created from the existing algorithm is corrected and rectified, so the algorithm is known as low latency corrective feedback algorithm. Based on the constant feedback from output, the corrections are made to reduce the latency (delay), irrespective of the iteration count size. The data bit stream is corrected repeatedly using the parity check matrix and the generator matrix is given to the final output as the final corrected signal.

COMPRESSED SENSING:

Compressive sensing is a signal processing technique. It is also called as compressed sensing, compressive sampling or sparse sampling. The compressive sensing is depending upon the knowledge about a signal to obtain a compressed representation. Compressive sensing is a signal processing technique used for reconstructing a signal. This signal is efficiently acquiring by finding the solutions to underdetermined liner systems. The sampling and dimensionality reduction in signal is performed by compressive sensing under the assumption of sparsity. This sparsity has played a very important role in modern signal processing and that utilizes the sparsity of signals

GET METRICS:

It is a measurement used for the calculation of the signal parameters. These metrics include coherence, sparsity, recovery error, correlation, recovery time, processing time, compression ratio, and phase transition diagram. They cover the most important aspects of the three compressive sensing processes in terms of time, error rate and cost.

REMOVE NOISE:

Noise reduction is the process of removing noise from the signal.Noise reduction technique exists for audio and images.Noise reduction algorithm ay distort the signal to some degree.All signal processing devices ,both analog and digital,have traits that makes them susceptible to noise.Noise can be random or white noise with an even frequency distribution,or frequency dependent noise introduced by a device mechanism or signal processing algorithm.

IV. SYNTHESISED RESULT

The proposed VLSI architectures of IPA and LLCF algorithms are implemented both in

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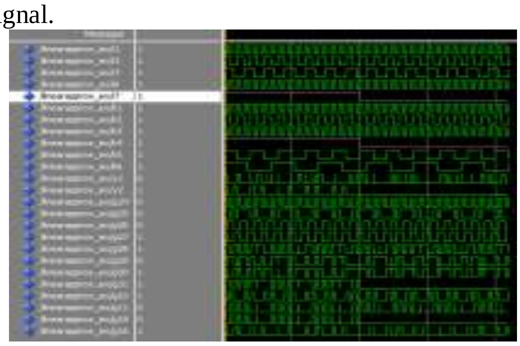
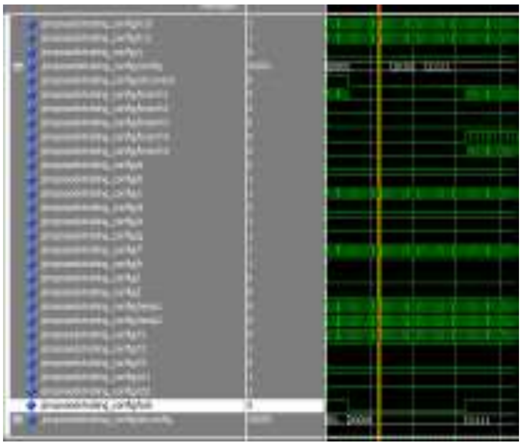
ASIC
and FPGA environments. Since there are no prior implementation for BCS in the literature, we compare the proposed designs with implementations of OMP from the literature. The sparsity of an LDPC matrix which is equal to 64. The results are compared with those of some instances of existing related architecture. The computations involved are all integer operations and the hardware consumption of the proposed designs independent of the sparsity level K unlike OMP. Since the proposed architecture is fully parallel, each iteration takes a single clock cycle. So, the number of clock cycles the design takes to reconstruct the signal is equal to the number of iterations.The waveform of the existing method with the IPA algorithm is being synthesized. Thus this output is result of the existing method have less accuracy and require more time.Thus, the waveform of the binary compressed sensing has been synthesized with the help of the MIPA the time efficient and less complex result have been obtained.

Thus from the below given figures, it can be inferred that the time interval of the waveforms in the proposed system signals are significantly reduced when compared with the existing system signal.



RESULT WAVEFORM OF EXISTING SYSTEM



RESULT WAVEFORM OF PROPOSED SYSTEM

V.CONCLUSION

VLSI architecture to realize IPA for BCS has been proposed. The algorithm is further modified to reduce its complexity for which VLSI architecture has been developed. The recovery performance of the proposed MIPA algorithm has been demonstrated on a standard LDPC measurement matrix. The proposed designs are implemented on both ASIC and FPGA platforms, demonstrating their high frequency of operation and low reconstruction.

VI. SOME OF THE ADVANAGES FROM THE ABOVE RESULTS

• Low Latency.
• Low Complexity.
• The orientation field refinement model plays a major role in this improvement in performance as it increases the number of directionless pixels in the flat area while enhancing the orientation field consistency in the region with edges.

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