International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347 - 6435 (Online) Volume 12, Issue 7, July 2023)

Review of Orthogonal Matching Pursuit for VLSI Applications

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***Abstract*— Matching pursuit has been applied to FPGA, VLSI, signal, image and video coding, shape representation and recognition, 3D objects coding,[6] and in interdisciplinary applications like structural health monitoring. Within all the practical applications, one critical issue that the compressive sensing needs to solve is how to reliably recover the original signals from the measured signal in an efficient way. Various algorithms have been proposed to reconstruct signals from the compressively sensed samples. There are several approaches, such as matching pursuit (MP). This paper presents review of orthogonal matching pursuit for VLSI applications.**

Keywords*— *FPGA-VLSI, OMP, Xilinx, Power, Area, Latency.

I. Introduction

The Matching pursuit algorithm iteratively looks for the measurement matrix column that is most relevant to the current signal estimation and then performs a simple calculation to update the estimated signal iteratively. The OMP algorithm incorporates a least-squares step to perform signal estimation, which is more accurate than MP. The least-squares step in OMP reduces the number of iterations but increases the complexity at each iteration. The SOMP applies multiple measurement vectors based on OMP, but it significantly increases the complexity and implementation cost. Because of its tradeoff between complexity and accuracy, the OMP algorithm is a good target for hardware implementation to obtain real-time compressive sensing signal reconstruction. The complexity of each iteration of the OMP algorithm is mainly due to a large number of inner product operations and matrix inversion operations. The overall complexity of the OMP is also mainly determined by the size of the measurement matrix and the amount of sparsity. The bottleneck of this algorithm is the solution to the least-squares problem [8].

Present a brief overview of the theory behind OMP-based signal reconstruction. Compressed sensing is a breakthrough theory that acquires and reconstructs a signal from fewer samples. It takes advantage of the fact that most natural signals are sparse in a specific transform domain. For example, consider image reconstruction, a common application of compressed sensing. If an image is transformed into the wavelet domain, where a few coefficients can represent most of the information, the remaining small coefficients can be approximated by zero. The reconstruction of the original signal x is an NP-hard.

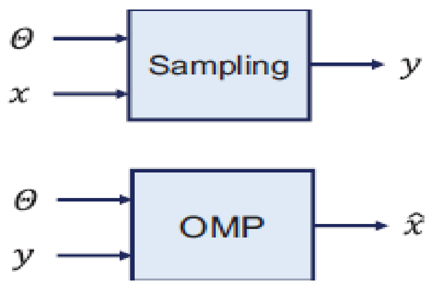

Figure 1: Sampling and OMP process

The greedy algorithms are directed to finding alternative solutions. The MP [7] is one of the most reliable greedy algorithms. The idea of the MP algorithm is simply to choose an atom (each column vector of the measurement matrix is an atom) that best matches the signal y from the measurement matrix A, construct a sparse approximation, and find the signal residual. Then, continue to select the atom that best matche the signal residual and repeat the iteration. The signal y can be represented by the linear sum of these selected atoms and the final residual.

The improvement of the OMP algorithm is that all selected atoms are orthogonalized in each iteration, which makes the OMP algorithm obtain the optimal solution in each iteration. The residual error in each iteration of the algorithm is orthogonal to the selected column vector, which makes the currently selected column vector linearly independent of the previously selected column vector, that is, the column vector will not beselected repeatedly in each iteration. This is why OMP is faster to converge than MP. The basic OMP [8] is now described. Generally, the basic idea of OMP is to find the indexes of all the nonzero components in the sparse coefficients through an iterative search and recovering one nonzero component by solving the least-squares problem at each iteration. In the nth iteration, the best atom in measurement matrix A is selected to match the observation signal residual r (initialized as the observation vector y). The best matching atom is selected and added to a subset of the observation matrix, named ˆA. The selected column does not need to be cleared because it is orthogonal to the residual r and will not be selected again in the next iteration. Based on the latest selected subset ˆA, a new estimated sparse coefficient and a new observation vector residual r are calculated through the least squares. In the next iteration, update ˆA by adding the atom that best matches the observation vector residual. Then, calculate and r until the end of the iteration. Finally, the reconstructed signal x can be obtained.

II. LITERATURE SURVEY

S. Liu et al.,[1] presented the projection-based atom selection orthogonal matching pursuit (POMP) algorithm, a threshold projection orthogonal matching pursuit (TPOMP) algorithm is proposed to improve the reconstruction accuracy and reduce the computational complexity. TPOMP algorithm expands the final support set dynamically and in parallel by setting threshold standards. The reconstruction simulation results show that the TPOMP algorithm exhibits a higher reconstruction success rate and higher reconstruction efficiency than the original POMP. The proposed reconstruction processor architecture is designed and implemented using Virtex UltraScale+ HBM VCU 128 FPGA under the configuration of M=256 , N=1024 , and K=36.

J. Li et al.,[2] The multipath fading problem can be overcome by Orthogonal frequency division multiplexing (OFDM) technique. However, combining OFDM technique with the multiple input multiple output (MIMO) systems increase the spectral efficiency, improve link reliability and increases the data rates. In wireless communications the channels are sparse and hence the estimation of these channels can be made by using compressive sensing (CS) recovery algorithm. The orthogonal matching pursuit (OMP) is one of the most well-known CS recovery algorithms. This work discusses MIMOOFDM channel estimation using OMP algorithm. The computational complexity of the OMP algorithm is very high and in order to accelerate the speed of the algorithm, VLSI architecture of OMP algorithm for estimating the MIMOOFDM channels has been designed and simulated using Xilinx 1S.2 Vivado HLX simulator.

S. S. Bujari et al.,[3] In our work, a Field-programmable gate array (FPGA) based architecture for compressive sensing using Orthogonal Matching Pursuit (OMP) algorithm is suggested. The storing and transmission of data is done and it will be made efficient when the sampled signal is compressed. Reconstruction of sampled data will be done using numerical computing intensive theorems which has many flaws. Implementation of Reconstruction stage is complex software implementation of these algorithms is awfully slow and consumption of the power will be more as the system has large number of layers due to most of the resource sharing at multiple levels.

G S Rajput et al.,[4] Random demodulation (RD) is one of the effective architectures utilizing compressed sensing (CS) theory to implement sub-Nyquist sampling. In this work, we present an implementation of orthogonal matching pursuit (OMP) algorithm for random demodulation based on field programmable gate arrays (FPGA) to facilitate real-time sub-Nyquist spectrum sensing exploiting RD. The present algorithm adopts an incremental QR decomposition (QRD) using Gram-Schmidt orthogonalization method to efficiently solve the least square problem (LSP) and is specified for random demodulation. The hardware implementation on the Virtex7 FPGA makes a good use of the resources to achieve a superior performance. Experiments show the present architecture can run at a frequency of 250MHz and reconstruct the signal within 317us for K=200, N=1000, m=40, which is applicable for scenarios requiring real-time spectrum sensing.

M. M. M. Nadzri et al.,[5] Compressive sensing (CS) is as an evolving research area in signal processing due to the advantages offered for signal compression. Based on the sparsity of signals, CS allows the sampling of sparse signals under the sub-Nyquist rate, and yet promises a reliable data recovery. To date, the implementation of practical applications of CS in hardware platforms, especially in real-time applications, still faces challenging issues due to the high computational complexity of its algorithms, hence leading to high power-consuming processes. There are several CS reconstruction approaches, and orthogonal matching pursuit (OMP) is one of the best and popular algorithms implemented. However, this algorithm faces two (2) major process issues: optimisation and the least square problem.

V. R. Kopparthi et al.,[6] This work presents a System on Chip (SoC) implementation of the standard Orthogonal Matching Pursuit (OMP) algorithm using matrix partition and Modified Cholesky factorization techniques. A fixed-point optimized hardware Intellectual Property (IP) of the OMP algorithm is designed using a high-level synthesis (HLS) tool. The execution time of the optimized fixed-point hardware IP for different sparsity is compared with the equivalent fixed-point and floating-point realization on the Zynq-7000 Field Programmable Gate Array (FPGA). Intel senor data is used for verifying the functionality of the SoC design. The experiment is carried out for signal length (N), compressed signal length (M) as 256 and 84 respectively with different sparsity factor (K) as 5, 10 and 15. The acceleration factor of 70 and 73 is achieved for the fixed-point and floating-point software realization of the OMP algorithm, respectively.

S. Roy et al.,[7] An efficient architecture of the orthogonal matching pursuit (OMP) algorithm is present to recover signals compressively measured at the sub-Nyquist rate. The present architecture is implemented on the field-programmable gate array (FPGA) for performance validation. In the place of matrix factorization-based pseudoinverse computation, Gaussian elimination (GE) is used to compute the signal estimate. A novel incremental Gaussian elimination (IGE) algorithm is present and used in the OMP algorithm. The present design is targeted to the Virtex6 FPGA device to compare with other reported works for K = 256 , N =1024 , and m =36 , where N is the number of samples, K is the measurement vector length, and m is the signal sparsity level. .

M. M. Ahmed et al.,[8] Due to the vast developments in the media communication field and the quality of the visual imaging, image data compression has been one of the most interesting field. The main purpose of the image compression is to produce a very low bit rate while achieving a high quality of the reconstructed images. Image compression are used for all fields of media communication such as medical image recognition, multimedia, digital image processing. There are different algorithms for compression and reconstruction. One of these methods is the Orthogonal Matching Pursuit that is used mainly in the reconstruction of the radar signal. This work discloses a new methodology for image compression and reconstruction to enhance the performance while at the same time reducing the bit data size.

P. Dave et al.,[9] Orthogonal Matching Pursuit (OMP) is the most widely used reconstruction algorithm in Compressive Sensing. The main challenge of the implementation is that it has more time-consuming reconstruction process due to its iterative nature and complex matrix inverse finding operation. This work presents a hybrid approach of implementing OMP on hardware using parallel blocks and optimum memory storage to expedite reconstruction, making it usable for applications where rapid reconstruction is desired. Present approach speeds up reconstruction process up to two times as compared to the previous work. The present approach uses the concept of adding the multiple matrix inverse blocks and sorting algorithm to find three most weighted columns. Increase in speed of operation comes at cost at hardware (size of hardware on silicon) increasing 3 times in comparison to conventional method.

S. Roy et al.,[10] A novel hardware architecture of orthogonal matching pursuit (OMP) is presented here, and the test is implemented on a field-programmable gate array (FPGA). The performance is evaluated by taking RADAR pulses that are compressively sampled synthetically using the random modulation preintegrator (RMPI). Basic test signals such as Gaussian pulse and its variations are taken as input to the RMPI. The output of the OMP algorithm is multiplied by the Gabor time-frequency dictionary to obtain the reconstructed RADAR signal. A novel method to implement the Gabor time-frequency dictionary is also presented. The OMP algorithm generates an estimate of a signal in m ($\geq$ M) iterations for an M-sparse signal.

X. Ge et al.,[11] presents architecture avoiding the complex square root unit mainly consists of some more basic computing units, where the computing process is broken down into several simple operations to map to the corresponding hardware for pipelining. The present implementation based on Xilinx Kintex-7 FPGA exploits the parallelism by a well-planned workload schedule and reaches an optimal tradeoff between the latency and frequency. The experimental results demonstrate that the present architecture can run at a frequency of 210 MHz with a reconstruction time of 238 μs for 36-sparse 1024-length signal, which improves the signal reconstruction speed by 1.43× compared to the state-of-the-art implementations.

S. Liu, et al.,[12] presents an efficient complex valued system hardware architecture of the recovery algorithm for analog-to-information structure based on compressive sensing. The present architecture is implemented and validated on the Xilinx Virtex6 field-programmable gate array (FPGA) for signal reconstruction with N = 1024, K = 36, and M = 256. The implementation results showed that the improved OMP algorithm achieved a higher RSNR of 31.04 dB compared with the original OMP algorithm. This synthesized design consumes a few percentages of the hardware resources of the FPGA chip with the clock frequency of 135.4 MHZ and reconstruction time of 170 μs, which is faster than the existing design.

III. CHALLENGES

There are the followings problems which is observed-

- GPU-based implementation does not facilitate the normal flow of data to the host as it faces a major problem of intermittent memory bandwidth between the main memory and the GPU. More critically, it is unable to achieve sufficient real-time decisions on the recovered signal. Therefore, it is very significant to present field-programmable gate array (FPGA) as a solution that connects to the analog front-end device to process the signals in real-time mode.
- The trade-off between computational complexity and accuracy is the main consideration for an efficient CS reconstruction algorithm. Currently, numerous algorithm approaches have been present to reconstruct the original signal from its compressed measurements in real-time.
- Convex and greedy approaches are the two most used algorithms. The convex approach is more complex and time-consuming and is inefficient for real-time implementations, but it promises better results in terms of accuracy. The alternative to convex is the greedy approach, which has less complexity and faster. Its algorithms run in a greedy iterative manner by searching for closely correlated values in each iteration.

The performance issue related to the high FPGA area, high latency and more power

IV. CONCLUSION

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The performance issue related to the high FPGA area, high latency and more power.

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