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#### An Architecture for Hardware Realization of Compressive Sensing Gradient Algorithm

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# Introduction

- Compressive sensing (CS) atracts significant research interest in last decade. Idea is to reconstruct sparse signal from reduced set od samples (measurements).
- Sparse signals are of interest in many applications like radars, sonars, biomedicine, etc.
- Two main research directions in CS:
  - 1. How to take measurements

#### 2. How to reconstruct signal

• This paper consider an arhitecture for hardware realization of gradient based reconstruction algorithm for sparse signals

# **Reconstruction algorithms**

- There are many groups of algorithms that deals with sparse reconstruction problems: pursuit methods, convex relaxation, nonconvex relaxation, brute force based methods
- Convex relaxation algorithms are the most commonly used ones and are based on  ${\rm I_1}\xspace$ -norm optimization
- This paper consider an hardware realization of one such algorithm [1]. Since considered algorithm is iterative, it is very important to find an optimal hardware realization in order to reduce computational time.

[1] LJ. Stanković, M. Daković, and S. Vujović, "Adaptive Variable Step Algorithm for Missing Samples Recovery in Sparse Signals," IET Signal Processing, vol. 8, no. 3, pp. 246 -256, 2014. (arXiv:1309.5749v1).

# Gradient algorithm

- Start with signal where all missing samples are set to 0.
- For each missing sample we form two signals:

$$y_1^{(k)}(n) = \begin{cases} y^{(k)}(n) + \Delta & \text{for } n = n_i \\ y^{(k)}(n) & \text{for } n \neq n_i \end{cases} & \Delta \text{ is used here in order to} \\ \text{decide should current} \\ \text{decide should current} \\ \text{sample value be increased} \\ y_2^{(k)}(n) = \begin{cases} y^{(k)}(n) - \Delta & \text{for } n = n_i \\ y^{(k)}(n) & \text{for } n \neq n_i \end{cases} & \text{or decreased} \end{cases}$$

and calculate approximation of measure gradient as:

$$g(n_i) = \frac{\mathcal{M}_p\left[T[y_1^{(k)}(n)]\right] - \mathcal{M}_p\left[T[y_2^{(k)}(n)]\right]}{2\Delta}$$

T is signal transformation to sparse domain

• Form gradient vector G and adjust missing sample values:

$$y^{(k+1)}(n) = y^{(k)}(n) - \mu G(n)$$

#### **Block scheme**







### **Correction block**



**Clock cycles** 

- Square root block 49 clock cycles (25 calculation, 24 issue rate)
- FFT block log<sub>2</sub>N clock cycles, where N is signal length
- All other blocks are elementary operations which could be finished within few cycles.
- Note that, all clock cycles are sumed within one iteration of algorithm, and obtained number is multiplied with number of iterations

# Conclusion

- Hardware implementations are of big importance for real applications
- One of the most important parameters which is used to determine the quality of proposed implementation is speed. So, it is used here as the measure of quality
- Proposed architecture is suitable for FPGA realization since realizations for all used blocks already exists
- Next step in our research will be to implement proposed realization on hardware

Thank you

#### **Questions**?