

Adaptive compressive sensing techniques for low power sensors

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Project Overview and Description

• Project description:

 Our current research indicates adaptive compressive sensing (ACS) is an attractive power saving technique for low-power biomedical sensors; The proposed efforts investigate circuit techniques to implement ACS at sensor nodes

• Specific problem to be addressed:

 How does a *simple* sensor node decide *when* and *how* to adjust sampling size in ACS

• Proposed Solution:

Using *low-power & low-accuracy* analog wavelet transform circuit to monitor signal sparsity variations

• Target Applications:

 Low-power biomedical sensors that form a body area network and communicate with mobile devices, such as smartphones.

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Introduction to Compressive sensing (CS)

- The CS theoretical framework was developed around 2004. Since then, it has been rapidly applied in many applications.
- The Basic Idea:
 - for a signal vector, $\{x_1, x_2, \bullet \bullet \bullet x_N\}$, with size of N
 - if it is sparse in some basis $\boldsymbol{\psi}$
 - Then, the signal can be acquired and reconstructed by taking only M measurements and M<<N

Benefits of CS

- Sampling signals at rates below the Nyquist–Shannon rates
- Sensing reduced number of pixels when capturing image or videos

Signal Sparsity

 Sensor signal X (X has N terms) is projected to another domain by matrix Ψ:

 $X = \Psi \alpha$

- The projected values is represented by vector α
- If only K terms in α are significant and K<N, signal X has sparse representation in domain Ψ



What signal to capture in CS

- Using a measurement matrix to capture signal X
 - Signal X is processed by another matrix operation

$$Y = \Phi \cdot X$$

- The size of Φ is N×M, and the value at each matrix element is **randomly** selected to be 1 or -1
- The size of Y is M (M<N) and Y will be the signal to be captured
- Note that this operation can be performed before or after analog to digital conversion
- The randomness is to satisfy the incoherent requirement,
 - Incoherent means if the signal is sparse in one (e.g. ψ) domain, it must be dense in another (e.g. ϕ)

How to recover Signal X from Y

- Receiver knows ψ and ϕ matrix
- Y is the signal received
- Receiver solves the α values from the received Y signal by:

 $Y = \Phi \cdot \Psi \cdot \alpha$

- Since α has N terms and Y has only M (M<N) terms, there exists more than one solutions
- However, the solution with the least number of significant terms in α is often the right solution. Such a solution can be searched by convex optimization techniques
- Once α is solved, sensor signal X can be reconstructed by: $X = \Psi \cdot \alpha$

Adaptive Compressive Sensing (ACS)

- Currently, the majority of CS implementation is *non-adaptive*
 - Fixed sparse basis (ψ)
 - Fixed measurement pattern (ϕ , M)
 - These parameters are selected based on fixed assumption or prior knowledge about signal x characteristics
- Very recently, approaches that adaptively change the measurement matrix (ψ) based on the online learning of signal characteristics have been explored for complex systems, such image, video capturing systems.
- ACS for low-power sensor devices have not seen reported in literature

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Overview of our work in ACS

Target Applications

 Ultra-low power sensors to measure biomedical signals, such as EEG, ECG, EMG, etc.

Outcomes of the current phase research

- Demonstrated signal sparity variations over the time for such sensors
- Power estimation package is currently being developed for predicting how much power can be saved by ACS for such sensors

Research plan for the next phase

- Develop circuit techniques for implementing ACS
 - Using low-power & low-accuracy analog wavelet transform circuit to monitor signal sparsity variations

Approach

- Develop the proposed circuit using a 0.13µ
 CMOS technology
- Establish the relation between circuit output and desirable sampling size M



- Evaluate the effectiveness
- Demonstrate power saving by system-level simulation (ACS sensor power estimator being developed in the current efforts will be used in this task)

Sparsity variation study using continuous-time WT

• Results



Significant terms of EEG Signal



- Letters A-G represents the different times when the data samples are collected
- The percentage errors are the RMS errors used to determine the significant terms
- This indicates that the sparsity of these biomedical signals does vary over the time. Thus, it is possible to adaptively adjust the sampling rate (ACS)

Power Estimator for ACS sensor under development



Introduction to analog WT circuit

Analog wavelet transform (WT) circuit

– Using a group of filters which correspond to the wavelet functions with different scale σ values



- Difference between ours and others' approaches (why can we make it ultra-low power?)
 - Use circuit outputs as indicators for signal sparsity, don't reconstruct the original signal from circuit outputs
 - Relaxed accuracy requirement; don't have to be always on
 - Tolerance to "false positive results" (indicating signal dense, but sparse)

Circuit to be investigated

Generating sparsity indication signal



• Focus of the investigation:

- Circuit design
- The relation between circuit outputs and desirable sampling size
- evaluation of its effectiveness
- Investigating its lower bound on power consumption; comparing the power consumed (by the proposed circuit) and the power saved (by ACS)
- New circuit design techniques

Project Tasks/ Deliverables