

## Adaptive compressive sensing techniques for low power sensors

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**Project Overview and Description** 

# Project Description

investigate the need, benefits, and circuit
techniques to implement adaptive compressive
sampling schemes in sensors with compressive
sensing techniques.

## Problem

- Most compressive sensing sensors assume the sparsity of sensor signals is relatively stable and hence use fixed compressive sampling schemes.
- The sparsity of certain sensor signals may exhibit significant fluctuations. Thus, adaptive compressive sampling potentially leads to more power-efficient implementations.

## Approach

- Perform system-level simulation with using realistic sensor signals (Multi-parameter Intelligent Monitoring in Intensive Care database) to study the fluctuations of signal sparsity.
- Based on system-level power models, study the potential power saving by adaptively adjusting the compressive sampling schemes.
- Develop new circuit techniques to address the challenges on implementing adaptive compressive sensing (ACS).

#### **Project Status**

- Study of signal sparsity fluctuation is completed. It shows the validity of adaptive compressive sensing
- The investigation on potential power saving is complete. It indicates significant power can be saved by ACS
- Matlab simulation package for checking the applicability of ACS and potential power saving is available for member companies
- Current work focuses on the design of analog circuits to be used in ACS

### **Project Tasks/ Deliverables**

	Description	Date	Status
1	Investigating the applicability of adaptive compressive sensing and demonstrating the potential power saving	8/13	Completed
2	Improve and encapsulate the matlab programs into a simulation package	10/13	completed
3	Design of analog wavelet transform circuit	03/14	On-going
4	Establishing the relation between circuit output and desirable sampling size; evaluating its effectiveness	07/14	

#### **Executive Summary**

- Compressive sensing is emerging as a new technique in ultra-low power sensor design.
- Adaptive compressive sensing can potentially result in further power saving.
- The project investigates the need, benefits, and circuit techniques to implement adaptive compressive sensing schemes
  - An interesting application area of the developed technique is in the design of biosensors that are parts of body area network and communicating with mobile devices



Source: Baheti, P.K.; Garudadri, H.; "An ultra-low power pulse oximeter sensor based on compressed sensing," Sixth International Workshop on Wearable and Implantable Body Sensor Networks, pp. 144-148, 2009.

#### Signal sparsity

– Sensor signal X ( X has N terms) is projected to another domain by matrix  $\Psi$ :

$$X = \Psi \cdot \alpha$$



- The projected values is represented by vector  $\boldsymbol{\alpha}$
- If only K terms in  $\alpha$  are significant and K<N, signal X has sparse representation in domain  $\Psi$

- Incoherent sampling
  - Sensor signal X is processed by another matrix operation (incoherent sampling)

$$Y = \Phi \cdot X$$

- The size of  $\Phi$  is N×M and Hence the size of Y is M
- If X has a sparse representation with K significant terms in  $\Psi$  domain and  $\Phi$  and  $\Psi$  are incoherent, and the minimum size of Y is:

$$M = \mathcal{O}(K \log \frac{N}{K})$$

If K<<N, then M<N. Thus, sensing or sending signal</li>
Y, instead of X, will lead to low-power operations

- Signal recovery
  - Receiver solves the  $\alpha$  values from the received Y signal by:

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

- Since  $\alpha$  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  $\alpha$  is often the right solution. Such a solution can be searched by convex optimization techniques
- Once  $\alpha$  is solved, sensor signal X can be reconstructed by:

$$X = \Psi \cdot \alpha$$

- Investigating the fluctuations of signal sparsity
  - Matlab/Simulink models are developed to emulate compressive sensing operations.
  - The  $\Psi$  matrices used in the models are either Gabor or wavelet matrix
  - Realistic sensor signals from MIMIC (Multi-parameter Intelligent Monitoring in Intensive Care) database are used in simulation.

 Results: Variations of signal sparisty and measurement sizes

Signal	Block	1	2	3	4	5	6
Fetal ECG	М	357	597	449	419	329	407
	K	30	37	7	6	54	21
Con	М	443	961	977	857	969	385
Cap	К	114	116	97	178	116	41
Stress	М	191	209	201	187	575	193
	K	30	36	35	28	15	34
PPG	М	231	118	169	141	255	237
	K	38	41	45	42	38	36

• Results:



Variation Between the Maximum and Minimum Number of Samples for Recovery

 Wireless transmitter model used in estimating power saving by ACS



#### Power model parameter values used in this study

Circuit Block	Circuit Parameters	Values
	Ν	8
DAC	С	50fF
DAC	K	0.05
	f_conv	100KHz
	fc	40KHz
Filtor	Q	5
Filler	SNR	50dB
	η	1×10 <sup>5</sup>
	k <sub>mixer</sub>	10×10 <sup>-3</sup>
Mixer	G	0dBm
	NF	10dBm
	A <sub>1</sub>	1.4×10 <sup>-6</sup>
DLI	A <sub>2</sub>	1.6×10 <sup>-4</sup>
FLL	f <sub>LO</sub>	2.4GHz
	f <sub>ref</sub>	22MHz
	A	2.3
VCO	f <sub>osc</sub>	2.4GHz
	L	6nH
DA	η <sub>PA</sub>	28%
FA	P <sub>out</sub>	-3dBm

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### Simulation flow and results



#### Analog wavelet transform (WT) circuit

– Using a group of filters which correspond to the wavelet functions with different scale  $\sigma$  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)

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Generating sparsity indication signal



(a)

(b)

Establishing the correlation:

