Ultra-Low Power Design of Multimodal Bio-Signal Wearable Systems

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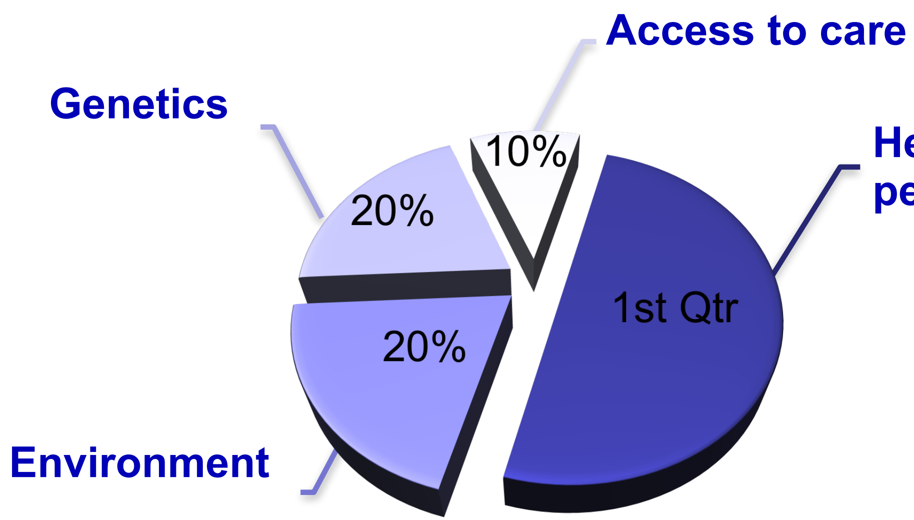
EPFL, Switzerland

ICT Summer School

Fiuggi, Italy July 9th, 2015

Pressing Changes in Healthcare Landscape and Economics Call for Personalized Healthcare



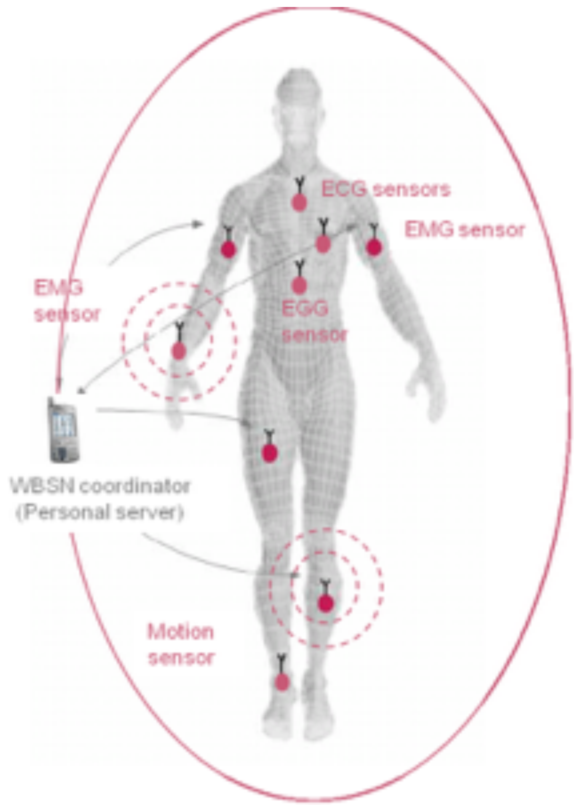
Determinants of health issues
(source: Institute for the future, Center for disease control and prevention, 2006)

- The burden of disease is shifting from diseases caused by infectious organisms to disorders with behavioral causes
- 50% of all deaths worldwide in 2006 and economic fallout in billions… expected to be 75% of gross domestic product by 2030
- This calls for a two-fold paradigm shift in health delivery:

Symptom-based	➔	**Preventive healthcare**
Hospital-centered sickcare	➔	**Person-centered healthcare**

WBSN is a major technology for wearable personal health systems

- Outfitting people with sensor collecting vital signals.
  - Many sensor: ECG, EMG, EEG, Accelerometer ,…
    - <> Huge bandwidth required
    - <> High power consumption
  - Increasing demand for long time monitoring
    - Autonomy and lifetime
- Main Challenge:
  - power efficient ✔
  - bandwidth ✔
  - small in form factor, light in weight



Wireless body area network (WBSN or WBAN)

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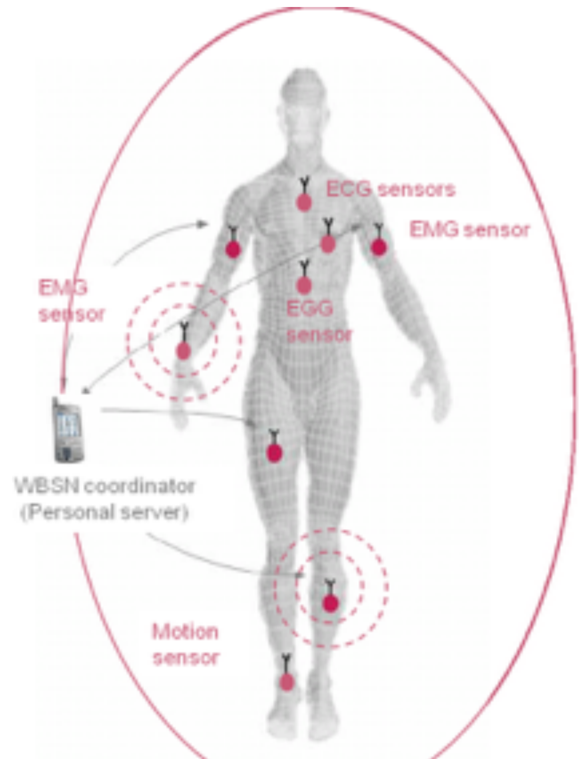
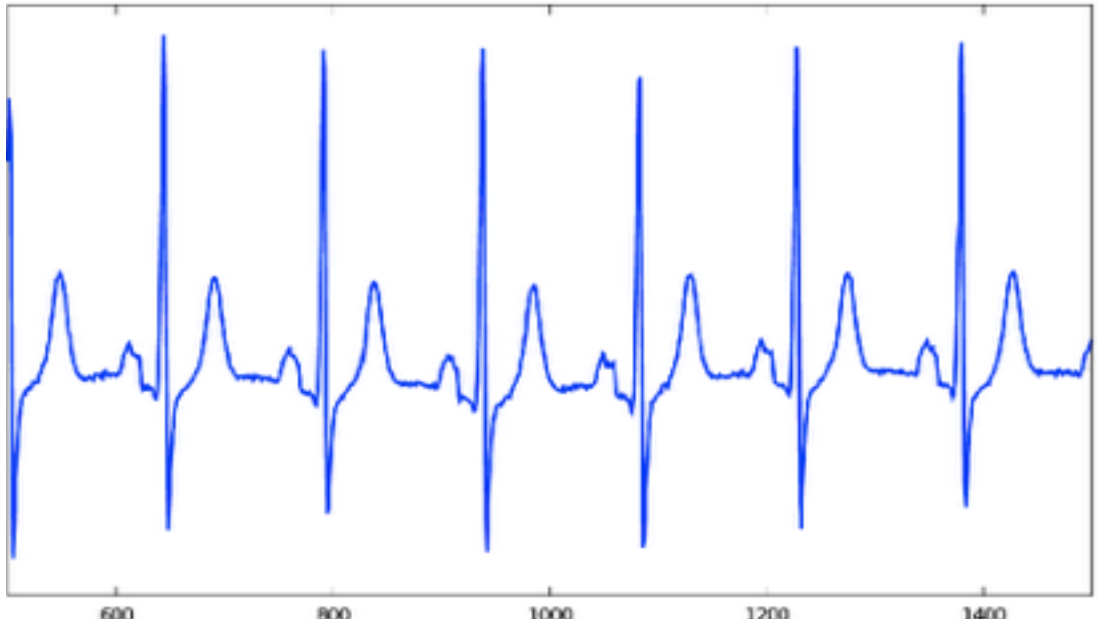


Multi-parametric bio-signals analysis:
How to design a WBSN?

State-of-the-Art WBSN Designs:Streaming of Raw Data

Long-term ECG monitor (Holter or event recorder)

Voltage



Time

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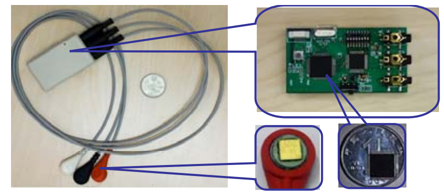
Long-term ECG monitor (Holter or event recorder)

MyHeart (Luprano,2006)



Kai,2011

Shimmer (2011)

Toumaz digital plaster (2011-13)

Streaming of only raw biosignal data

Health@Home (Sánchez, 2010)

MobiHealth (Halteren,2004)

TEMPO *(Barth,2009)*

Thiemjarus (2005-11)

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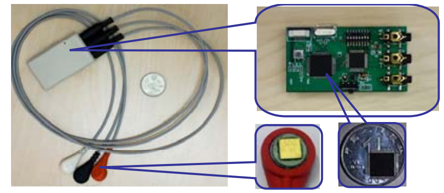

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Since the WBSN nodes do not do any processing, how much can they last? Only 2-3 days…

The Shimmer™ WBSN platform

- **TI MSP430 microcontroller**
  - 16-bit, 8MHz, 10KB RAM, 48KB Flash
  - ADC converters, DMA, HW multiplier
- **CC2420 radio**
  - 250 Kbps, ZigBee compliant
- **Sensors**
  - 3-channel ECG
  - Accelerometers and gyroscopes

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- **Sensors**
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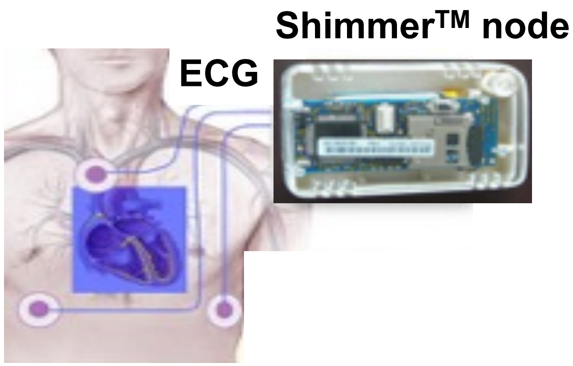
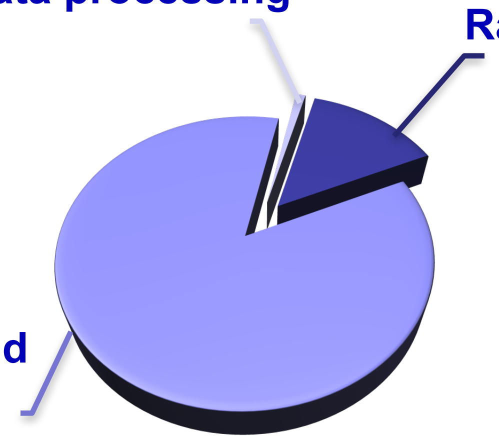
- **CONSTRAINTS:**
  - No floating point operation
  - No hardware division
  - Limited memory
  - Limited autonomy (rechargeable Li-polymer battery of 380 mAh)

Long-lived wireless ECG monitoring require a major breakthrough in the energy efficiency of WBSN nodes



1. **Can we reduce the data sensing/sampling cost and the amount of streamed data?**
2. **Can we embed automated analysis without compromising the system lifetime?**

- This wireless 1-lead ECG streaming monitor **lasts 134.6 h.**



Energy consumption breakdown

[Rincon et al., DATE '08 and TITB '11]

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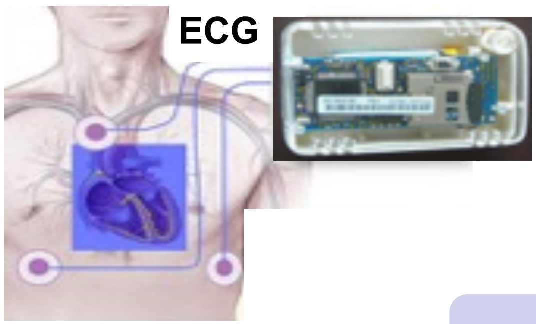

1. **Can we reduce the data sensing/sampling cost and the amount of streamed data?**
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Under stringent processing and memory constraints!

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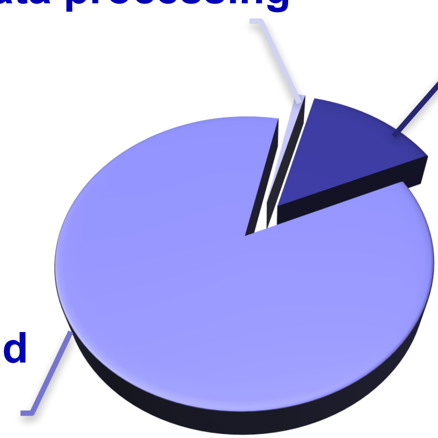

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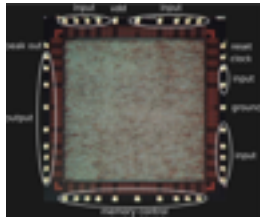
State-of-the-Art Smart WBSN: Embedded Processing

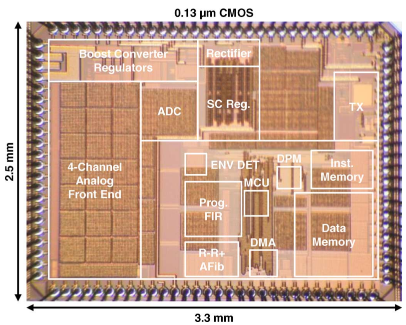
Shimmer
(shimmerresearch, 2010-13)



Heart Rate Monitoring
(Massagram, 2010)

Corventis's PiiX
(Corventis MCT systems, 2011-13)

Toumaz's Sensium Life
(Wong,2009)



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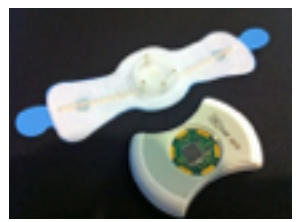

IMEC cardiac patch
(Yazicioglu,2009)

Holst Centre
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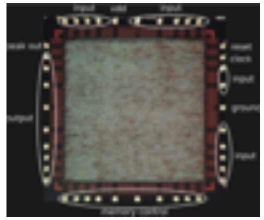

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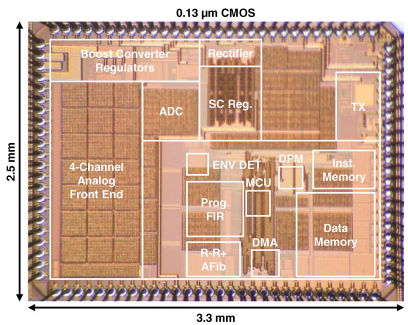

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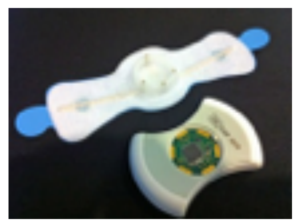

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Only simple filtering and one-lead input

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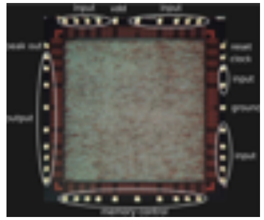

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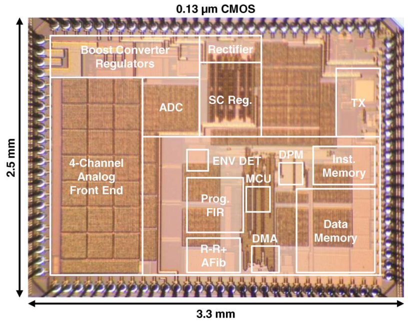

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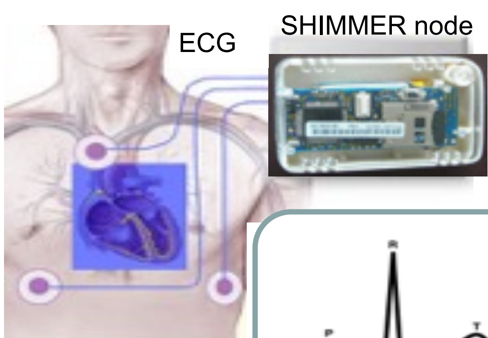
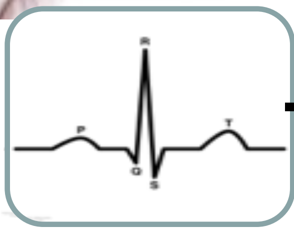
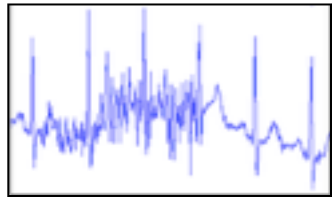
Only simple filtering and one-lead input

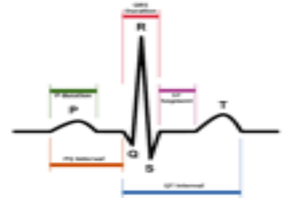
The goal from an ULP system-level perspective is to design:
(1) Long-lived and accurate multi-lead ECG monitoring
(2) Smart wireless personal health analysis systems

Our smart ECG sensor node concept for WBSN will capitalize on all 3 automatic processing algorithms



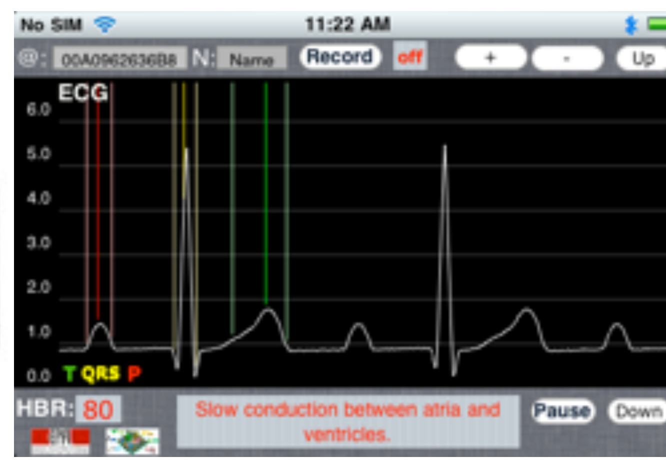






→ Noise filtering → ECG delineation → Feature Analysis (arrhythmia diagnosis) →

→ **Displays the received data**



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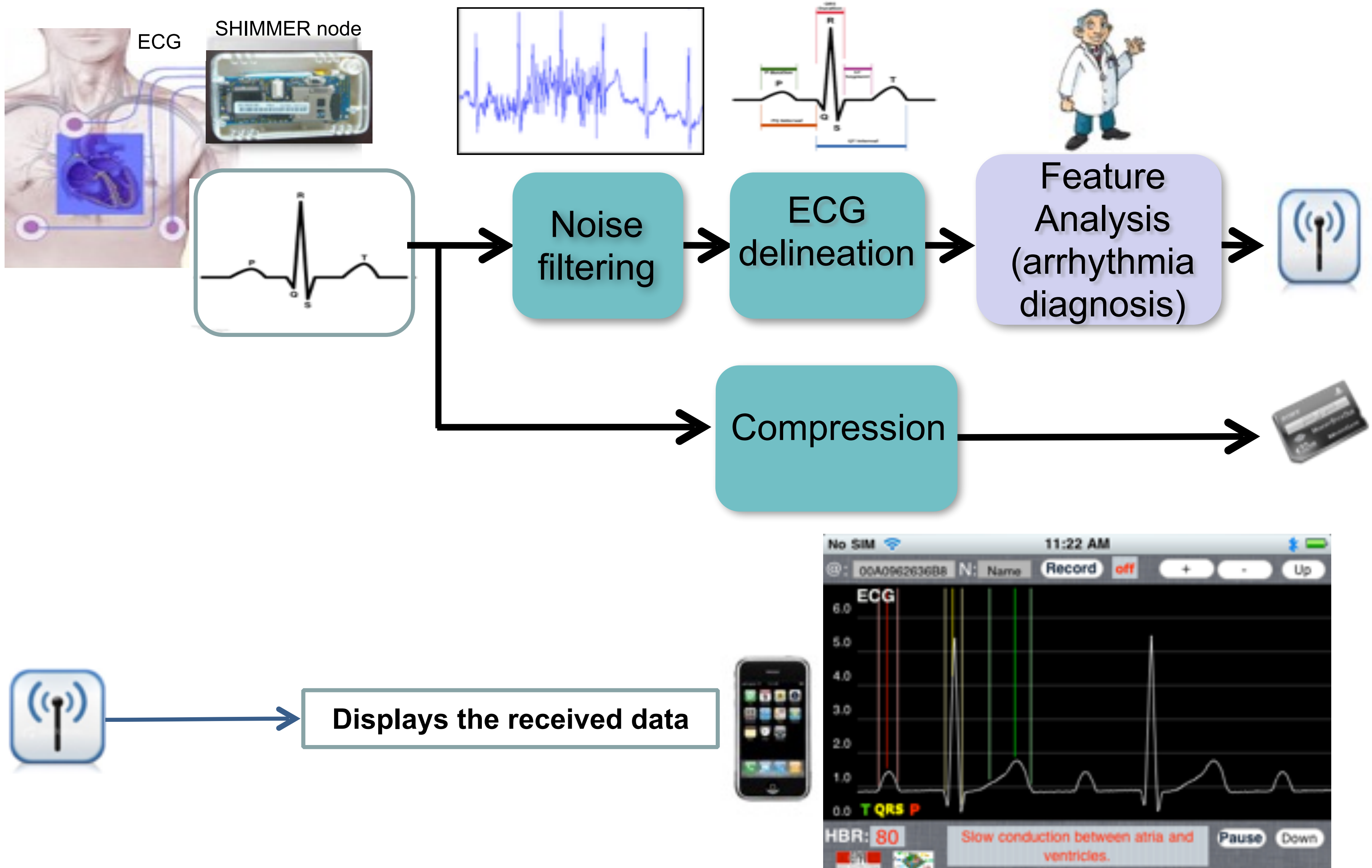
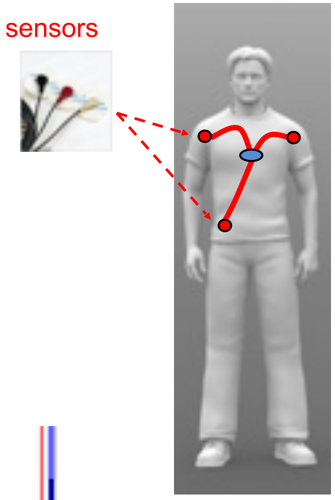
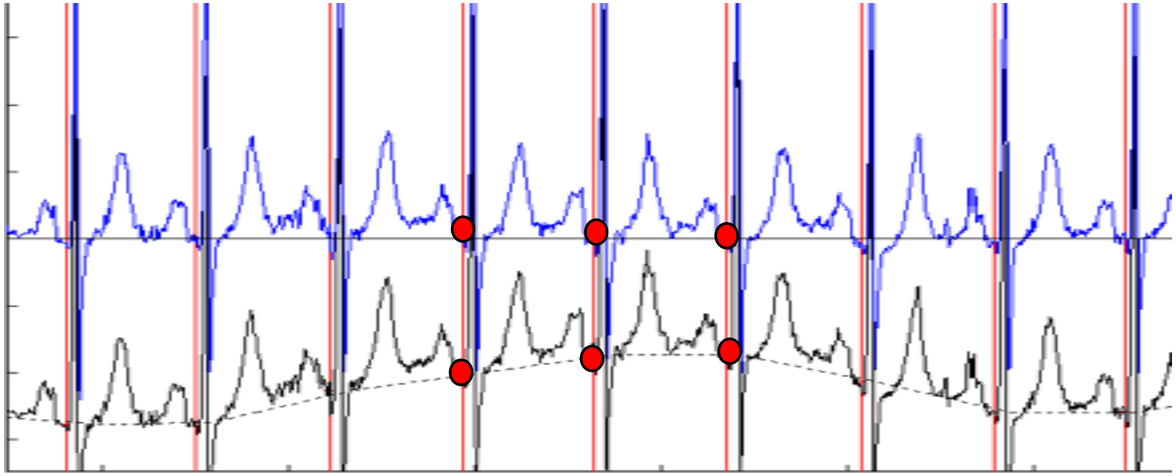


Selecting ECG filtering algorithms

- Baseline wander and muscular noise removal
  1. Cubic spline **[Rincon et al., TITB'11]**
     - Detect the knot of 3 consecutive beats
     - The curve fitting the 3 knots is the baseline wander
  2. Morphological filtering (**99.2% accuracy**)
     - Based on erosion and dilation operations
     - Baseline correction + noise reduction





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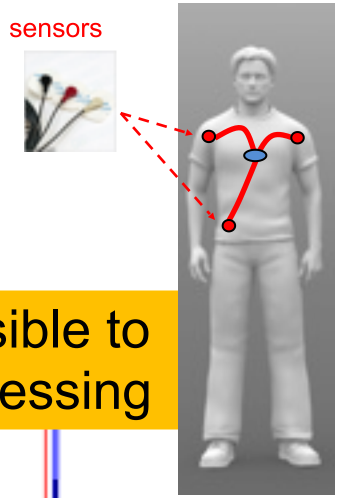
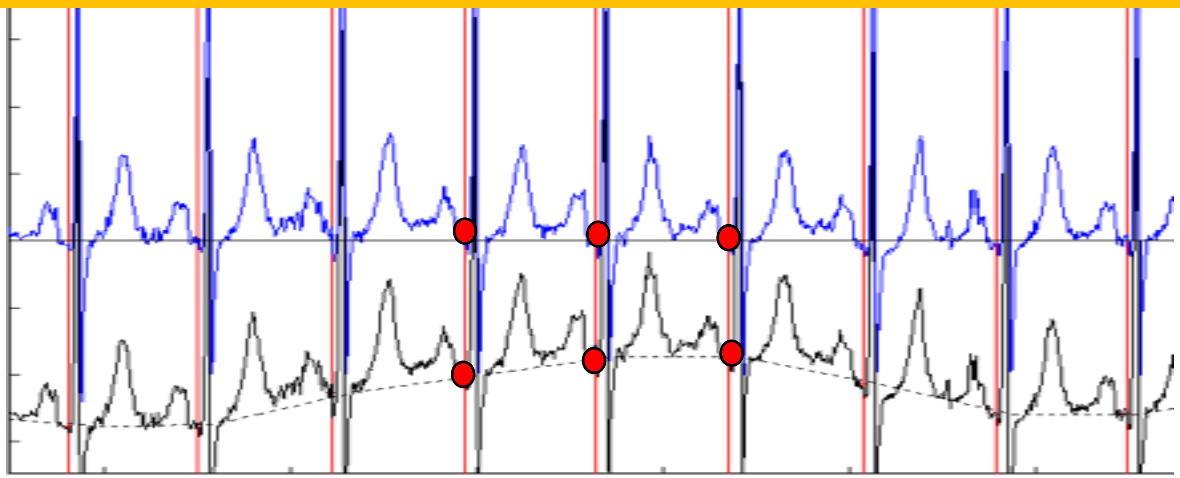
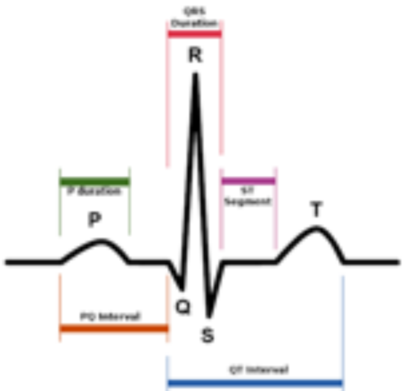


Moral of the story: knowing possible noise sources, possible to correct them with few sensors and “simple” signal processing



Embedded delineation of ECG characteristic waves



- Delineation is either done manually (by a cardiologist) or automatically (either by a bulky bedside equipment or offline on a PC)

- Delineation can be either based on a single lead or multiple leads

ECG_0 → Real-time single-lead delineator (discrete Wavelet transform)
[Boichat et al., BSN'09] → ECG characteristic waves timing and amplitude information

- **Optimizations for online operation:**
  - Processing of short blocks of ECG samples
  - Dynamically adapting underlying signal thresholds
  - Integer operations for fast implementation of complex functions (√)

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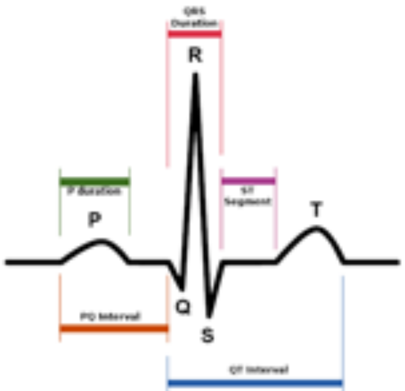

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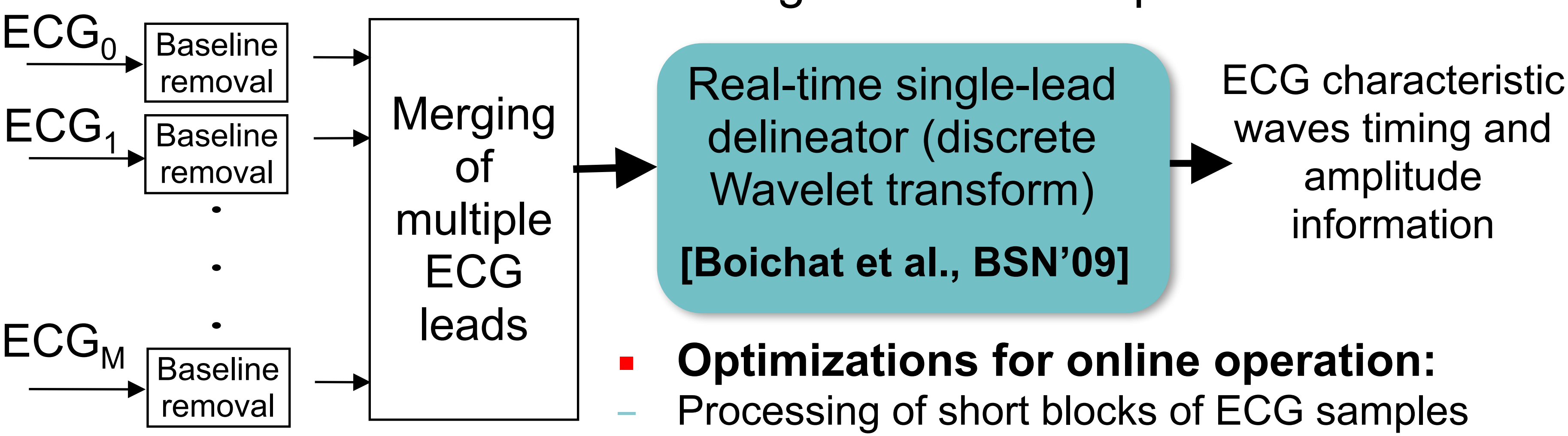

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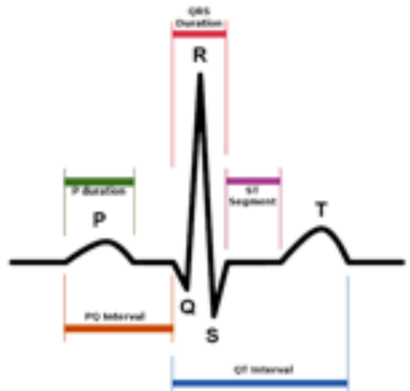

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Filtering

ECG_0 → Baseline removal
ECG_1 → Baseline removal
.
.
.
ECG_M → Baseline removal

→ Merging of multiple ECG leads → Real-time single-lead delineator (discrete Wavelet transform) **[Boichat et al., BSN'09]** → ECG characteristic waves timing and amplitude information

[Rincon et al., TITB'11]

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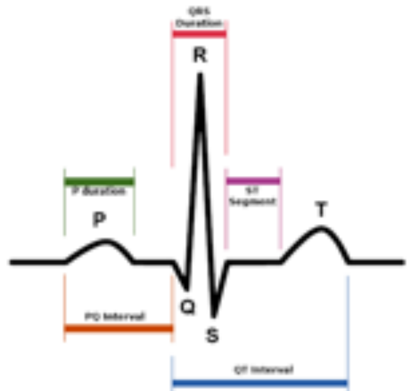

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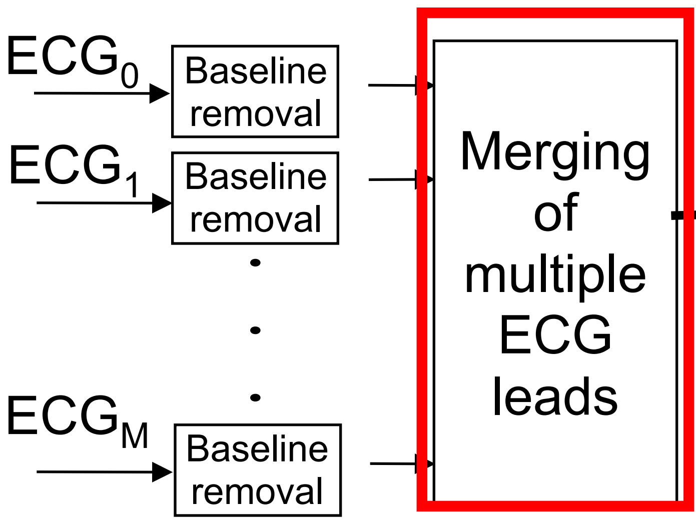
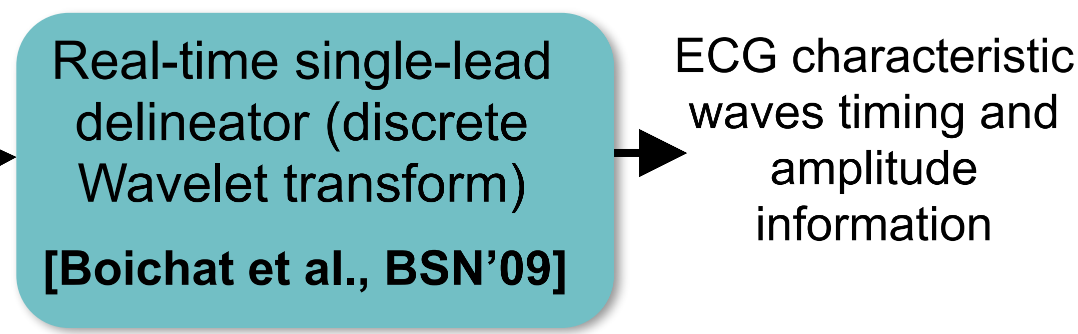
Root-mean-squared





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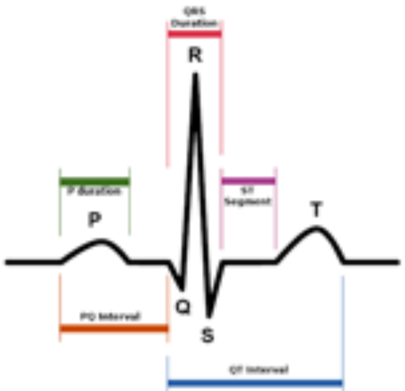

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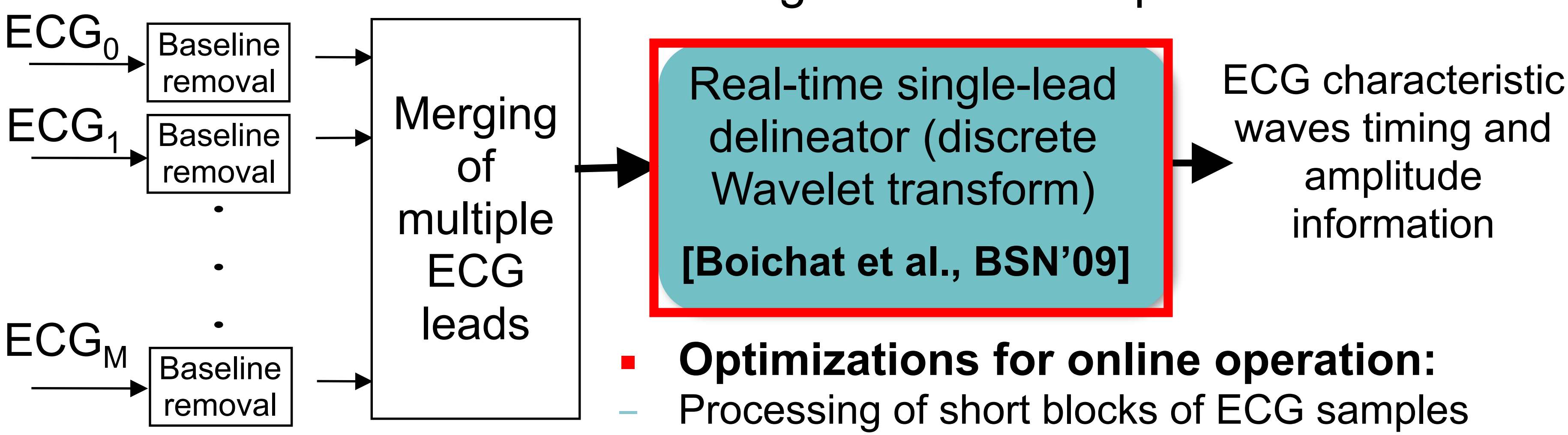

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Arrhythmia detection in WBSN systems

- Database of pathologies based on delineated points and thresholds
  - Defined at design time with doctors (few 100s of bytes of memory)
  - Applied at run-time by using a **simple look-up table**

$[QRS_{on}, QRS_{end}] \leq 0.10s$
$0.12s \leq [P_{on}, QRS_{on}] \leq 0.20s$
$T_{peak} > 0$
$[QRS_{on}, R_{peak}] < 0.03s$
QT interval rule
HBR variability
Atrial activity

Filtering → **ECG delineation** → **Arrhythmia diagnosis** →

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Filtering → **ECG delineation** → **Arrhythmia diagnosis** →

!

No issues of complexity or memory requirements, but need to develop **new adaptive classifiers** for each type of person

Biggest issue: Achieve efficient interaction with doctors!

Personal arrhythmia detection WBSN system

See video at: http://esl.epfl.ch/cms/lang/en/pid/46016

A Real-Time Wavelet-Based
Electrocardiogram Delineation System

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ArTeCS

Implementation results on the Shimmer node as WBSN system

- Real-time delineation demands limited requirements after careful algorithm optimization (computational load and memory footprint)

Algorithm	RAM usage	Buffers length	Execution time
Single-lead WT delineator	6.8 kBytes	512 elements	5%
Multi-lead WT delineator (morphological filter of baseline removal)	5.5 kBytes	256 elements	30.5% total (23% filtering, 2.5% multi-lead merging, 5% delineation)

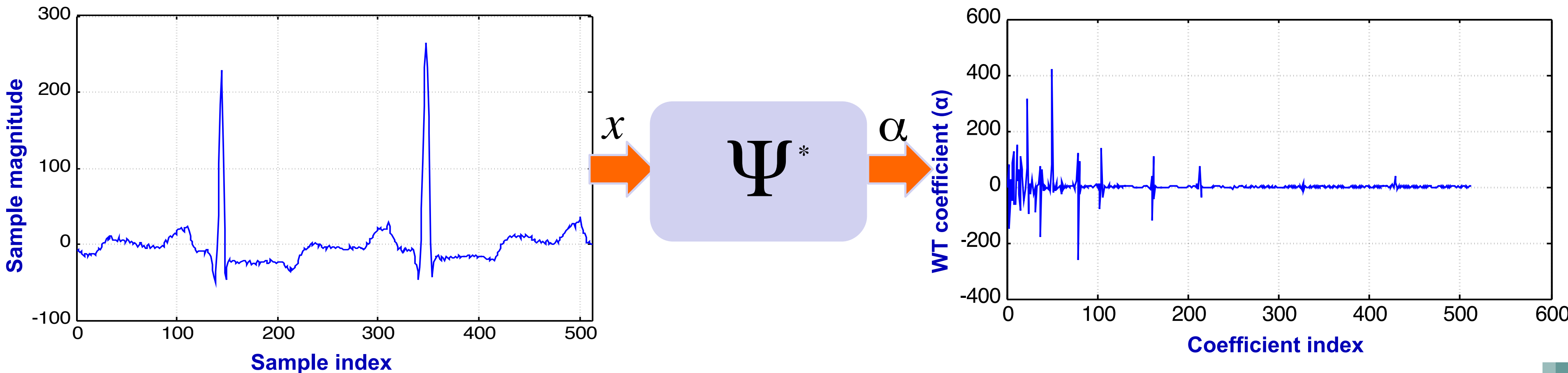
Execution of complex automatic ECG processing algorithms is possible

Small on-chip memory (10 kB) is the current limiting factor

Advanced on-chip processing gives real-time information about heart health with no impact on node lifetime: **more than 139 hours**

The electrocardiogram is a highly compressible signal

- ECG is highly sparse in the wavelet domain



- The Discrete Wavelet Transform (DWT) allows near-optimal compression of ECG signals

Orthogonal wavelet basis

Original ECG vector

$$x_N = \Psi \alpha_N$$

$$\|\alpha\|_0 = K << N$$

Coefficient vector

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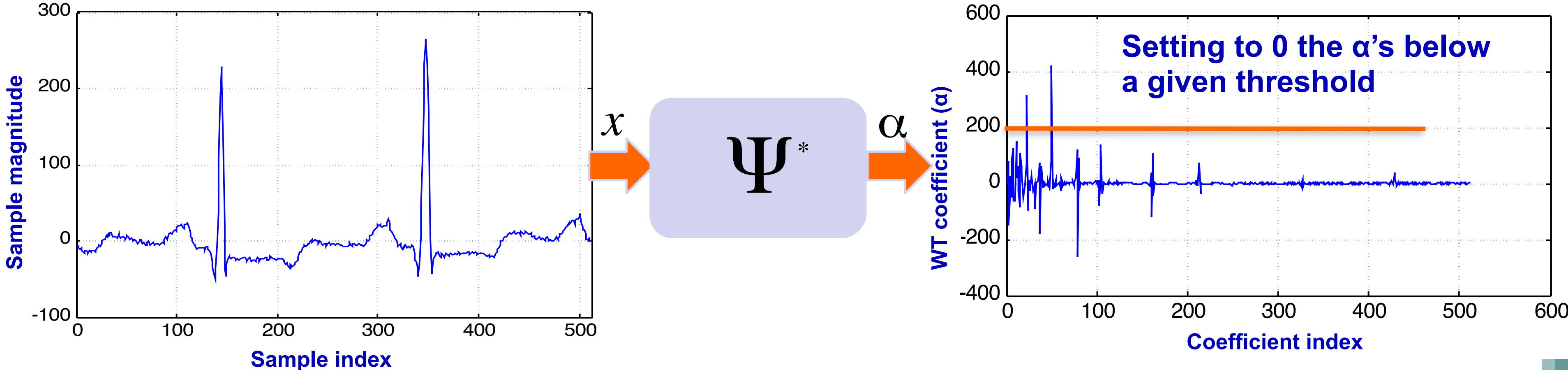
Thresholding-based DWT compression



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Coefficient vector

But can we create a "universally optimal" low-complexity compression scheme for ECG signals that works as well?

Compressed sensing (CS) is a new low-complexity sensing and compression paradigm for sparse signals

- Using CS it is sufficient to collect *M* (<<*N*) linear random measurements (samples)

Measurement/Sensing matrix (Gaussian random matrix)

$$\boxed{y_{M\times 1} = \Phi_{M\times N} \cdot x_{N\times 1}}$$

Measurement vector **Original ECG vector**

- Then, α can be recovered by solving the convex optimization problem:

$$\boxed{\min_{\tilde{\alpha}\in\Re^N} \left\|\tilde{\alpha}\right\|_1 \quad \textbf{Subject to:} \quad \left\|\Phi\Psi\tilde{\alpha} - y\right\|_2 \le \sigma}$$

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$$y_{M\times 1} = \Phi_{M\times N} \cdot x_{N\times 1}$$

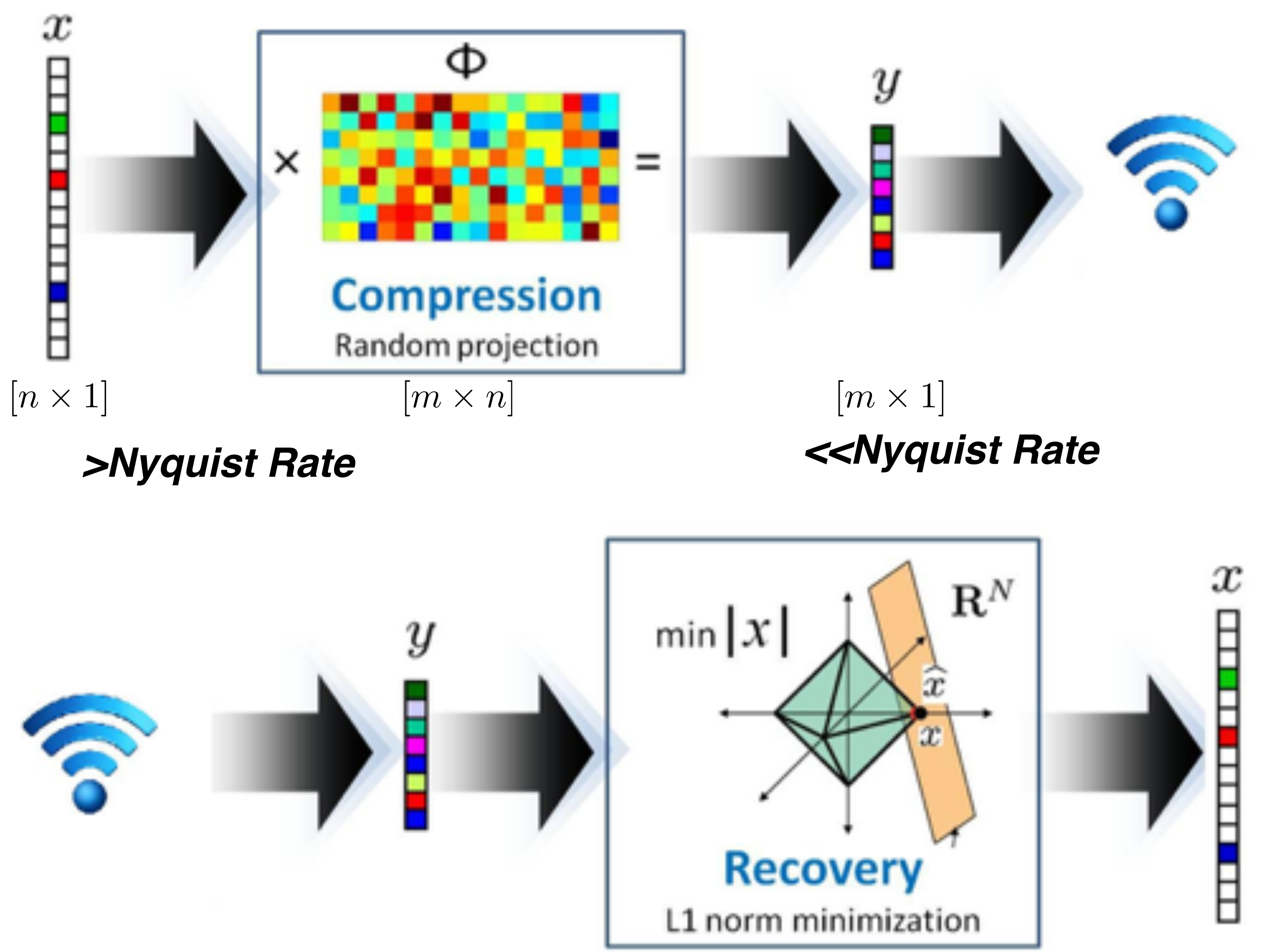
Measurement vector **Original ECG vector**

- Then probl

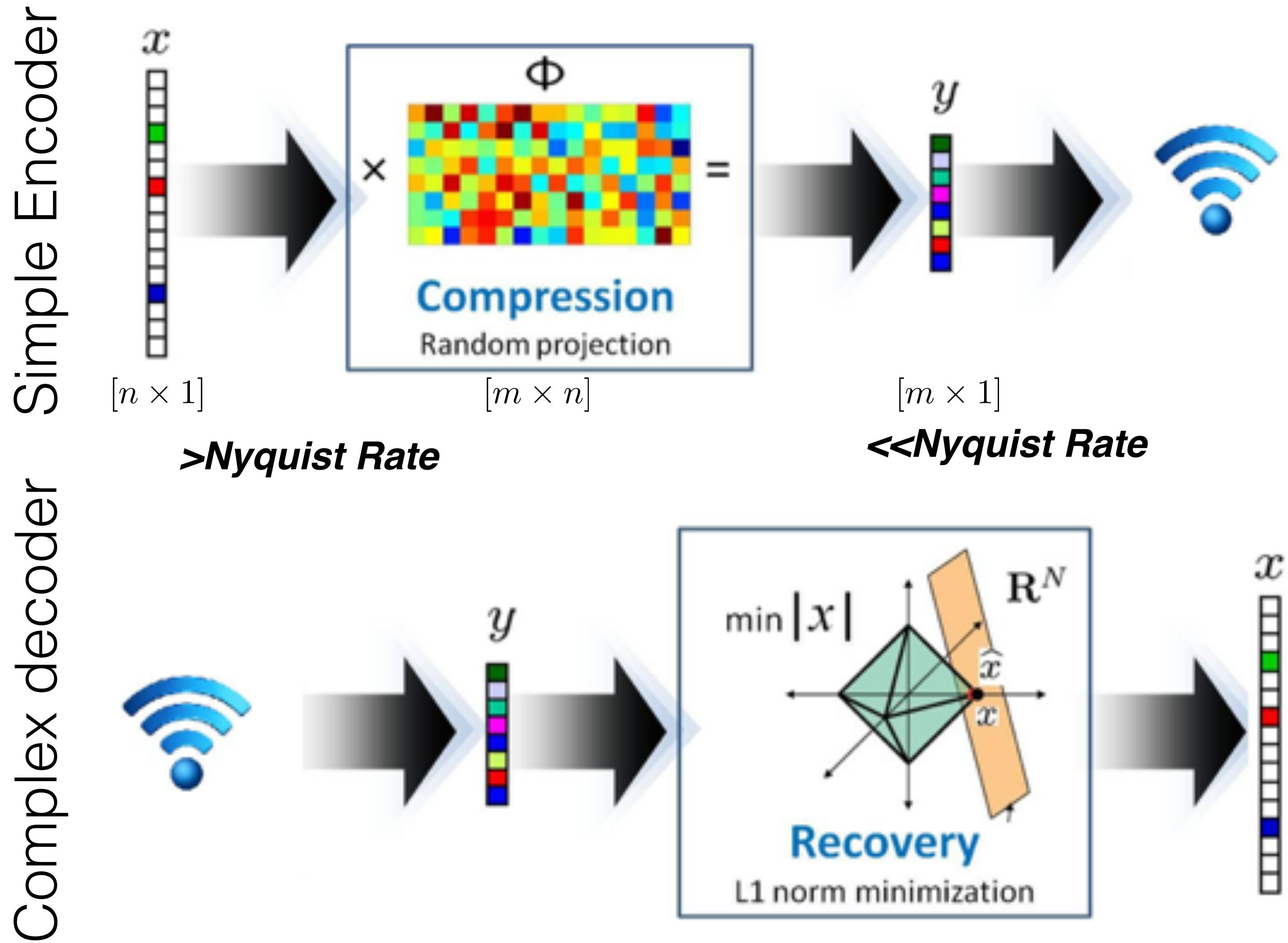
CS is attractive for real-time ECG compression on resource-constrained WBSN, but what about biosignal degradation due to CS reconstruction (in real-time)?

$$\min_{\tilde{\alpha}\in\Re^N} \|\tilde{\alpha}\|_1 \quad \textbf{Subject to:} \quad \|\Phi\Psi\tilde{\alpha} - y\|_2 \leq \sigma$$

Compressed Sensing



Compressed Sensing



Database, performance metrics and comparison

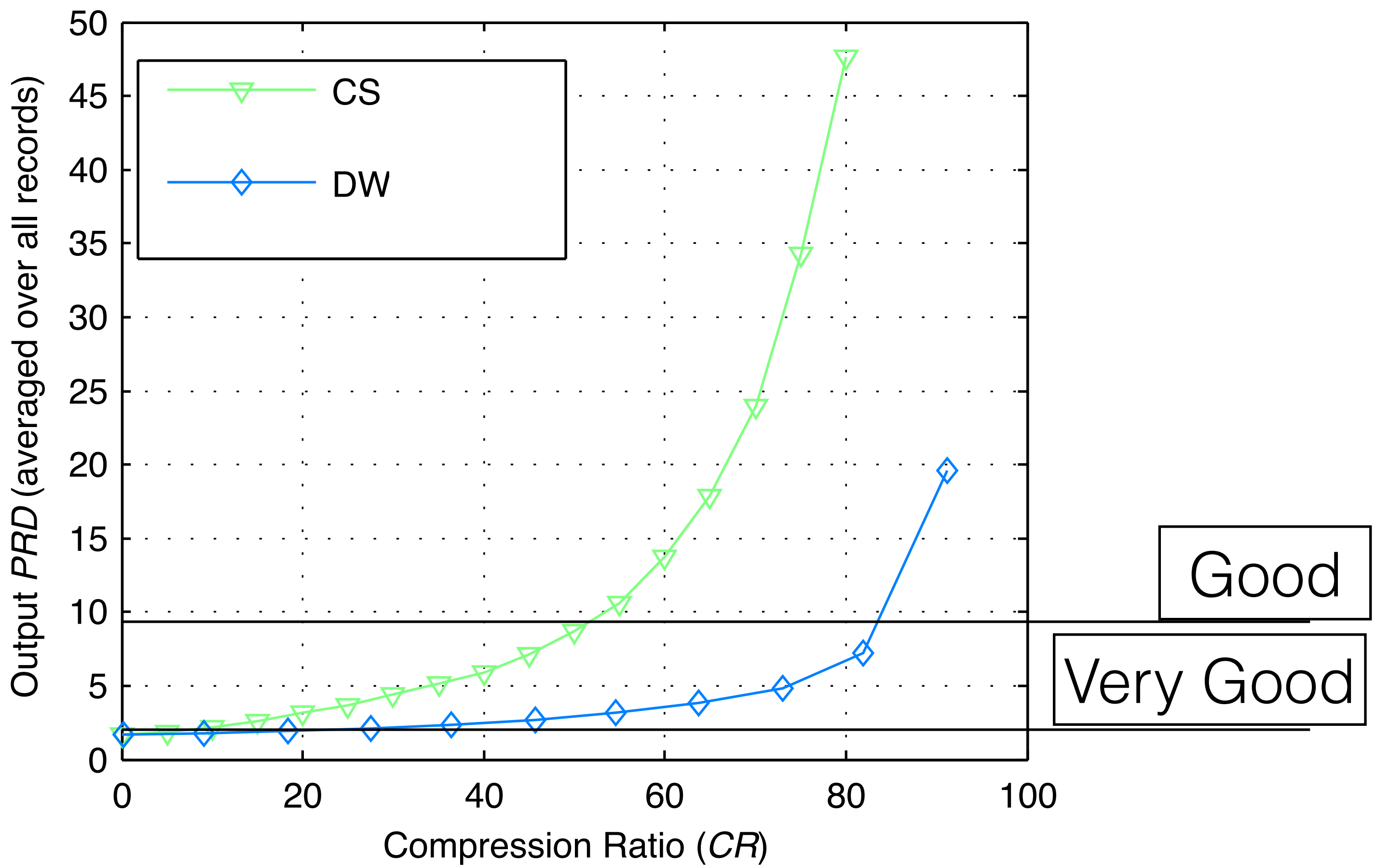
- MIT-BIH Arrhythmia database:
  - Contains 48 half-hour excerpts of two-channel ambulatory ECG recordings
  - Reference database for ECG compression studies
- Percentage Root Mean Square Difference (PRD) is defined as:

$$\boxed{PRD = \frac{\|\mathbf{x}-\tilde{\mathbf{x}}\|_2}{\|\mathbf{x}\|_2} \times 100}$$

$$\boxed{SNR = -20\log_{10}(0.01PRD)}$$

PRD	Reconstructed Signal Quality
0 ~ 2%	"Very good" quality
2 ~ 9%	"Very good" or "good" quality
9% <	Not possible to determine the quality group

CS is competitive in the low PRD range for high-fidelity compression



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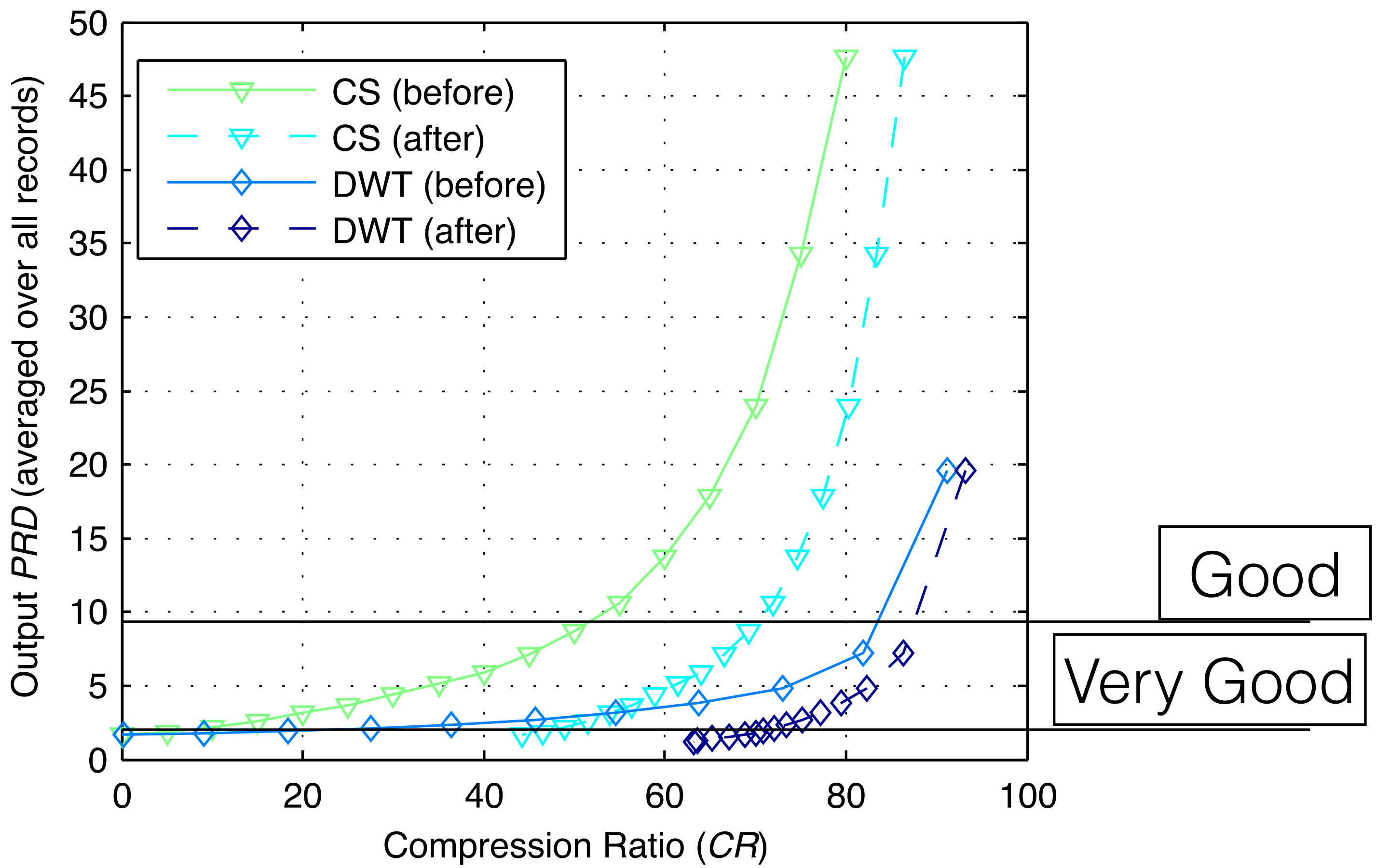
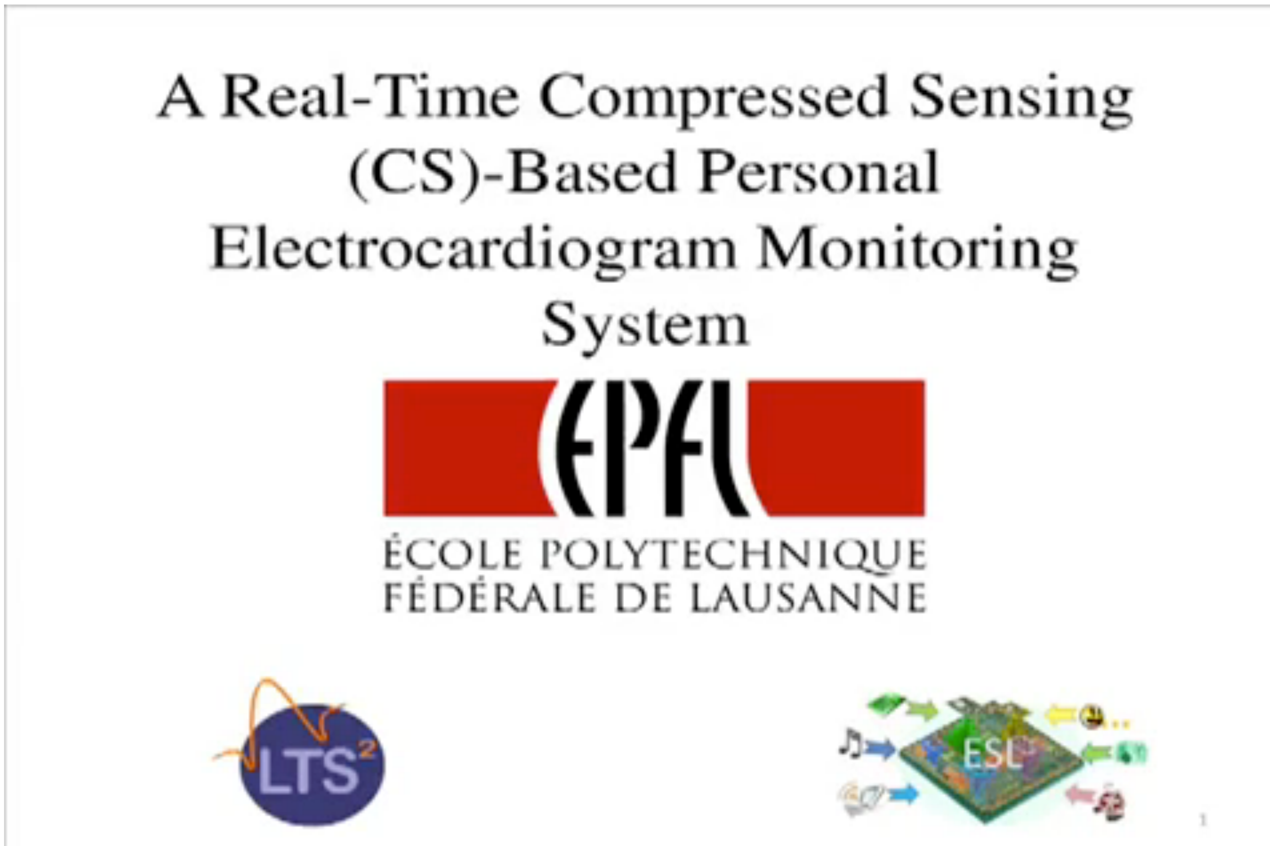


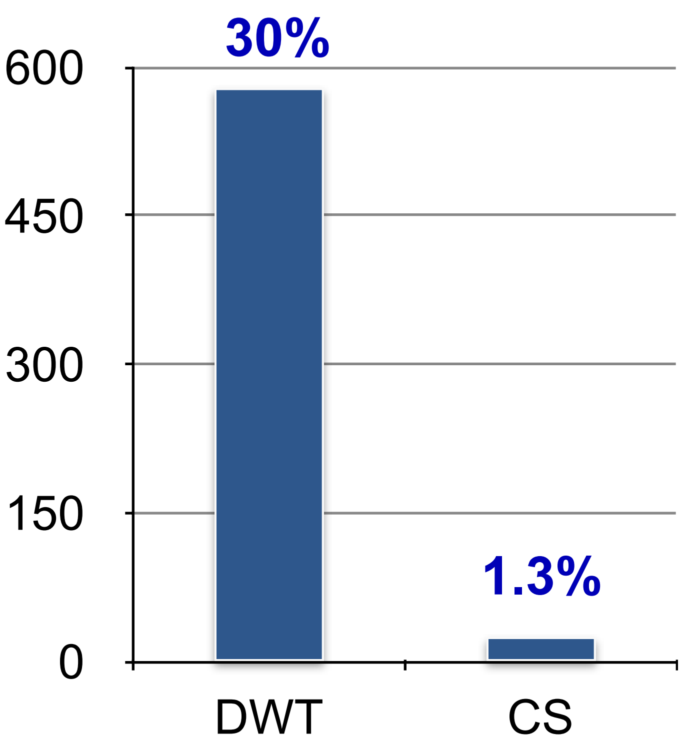
CS-based ECG WBSN (only 30% of ECG data kept)

See video at: http://esl.epfl.ch/page-42817.html



CS provides over a 23-fold reduction in execution time, but only 10% node lifetime extension

Code execution time



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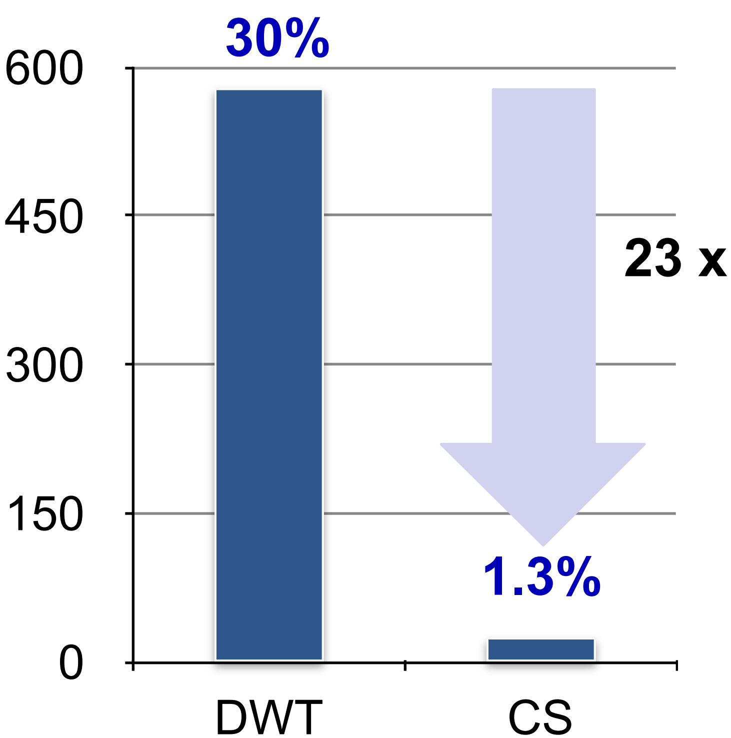

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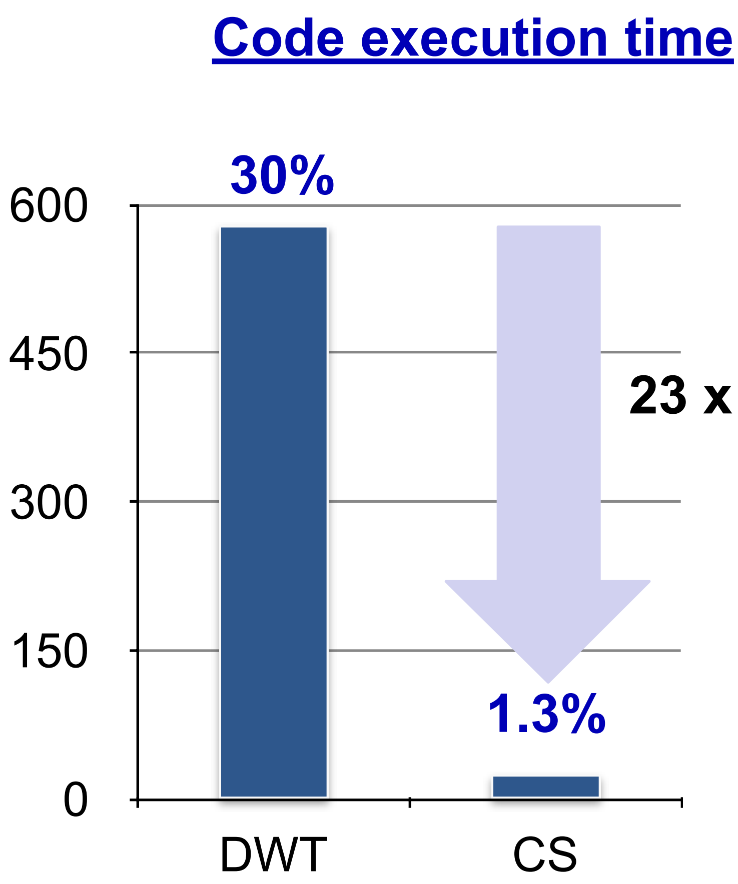

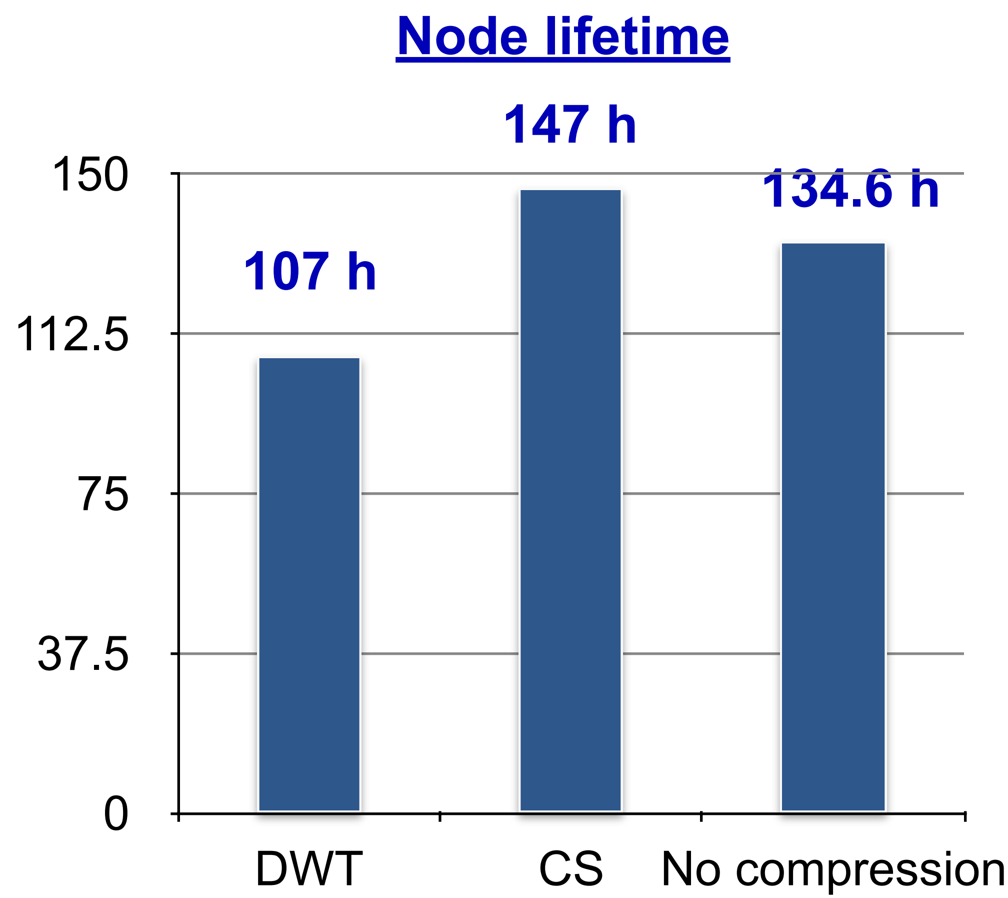

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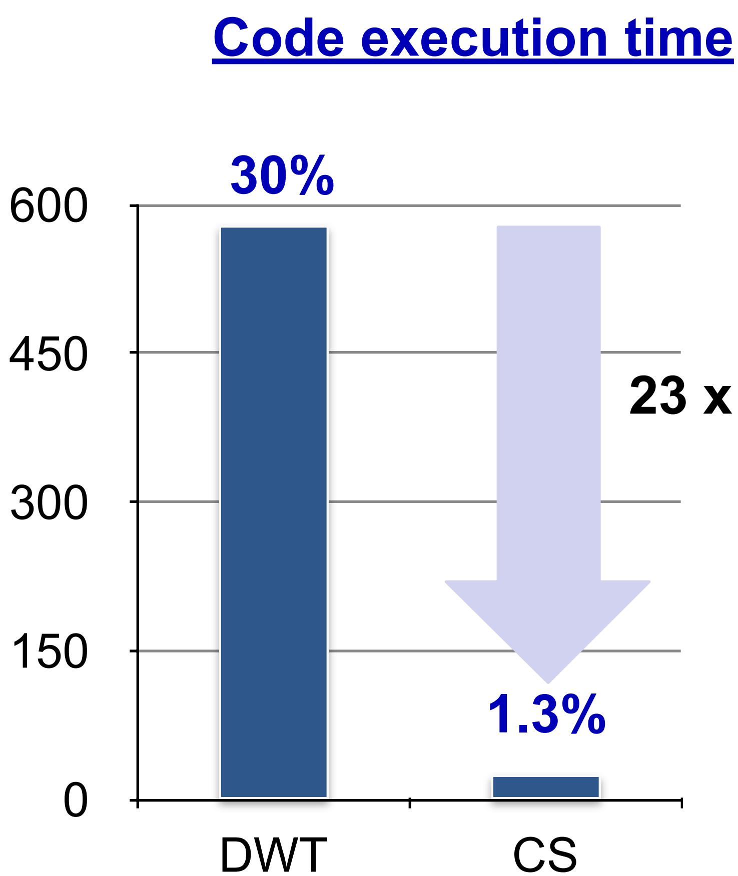

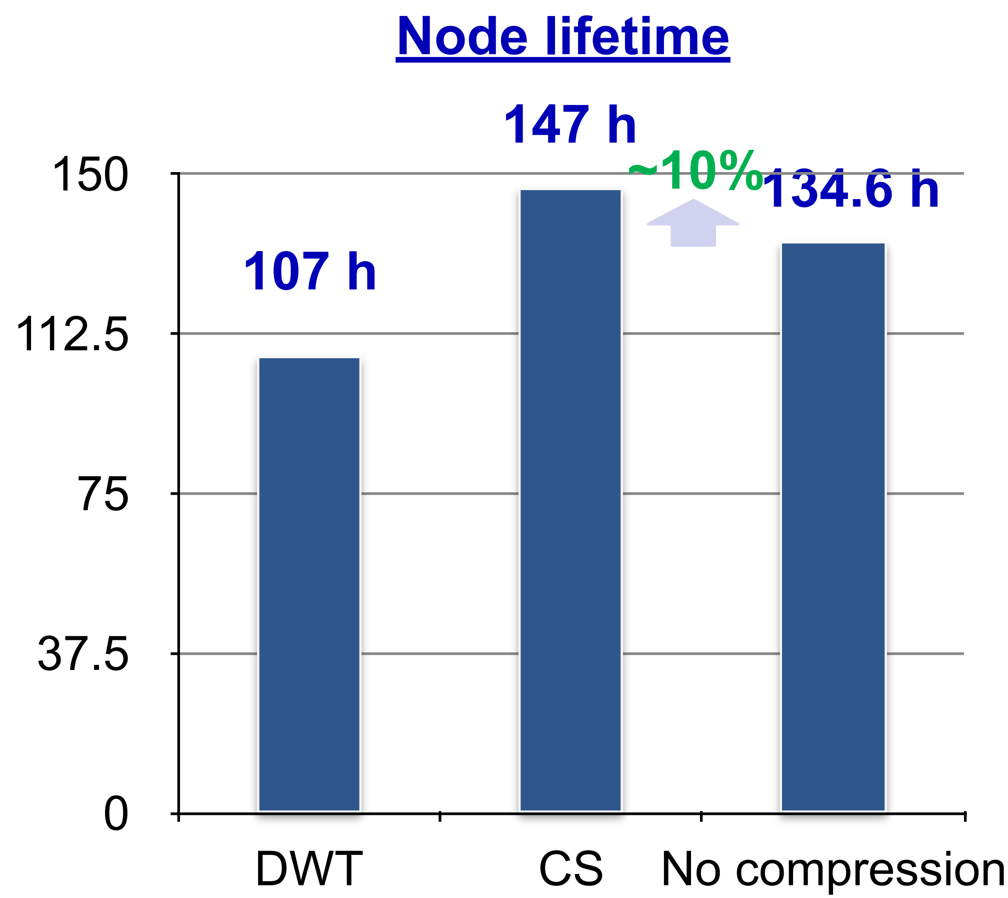

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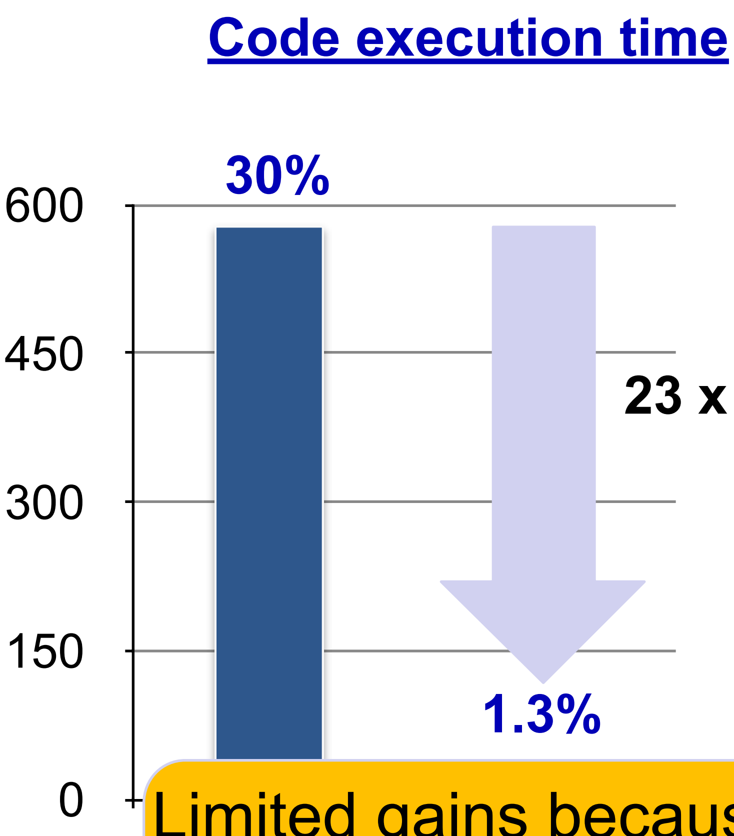
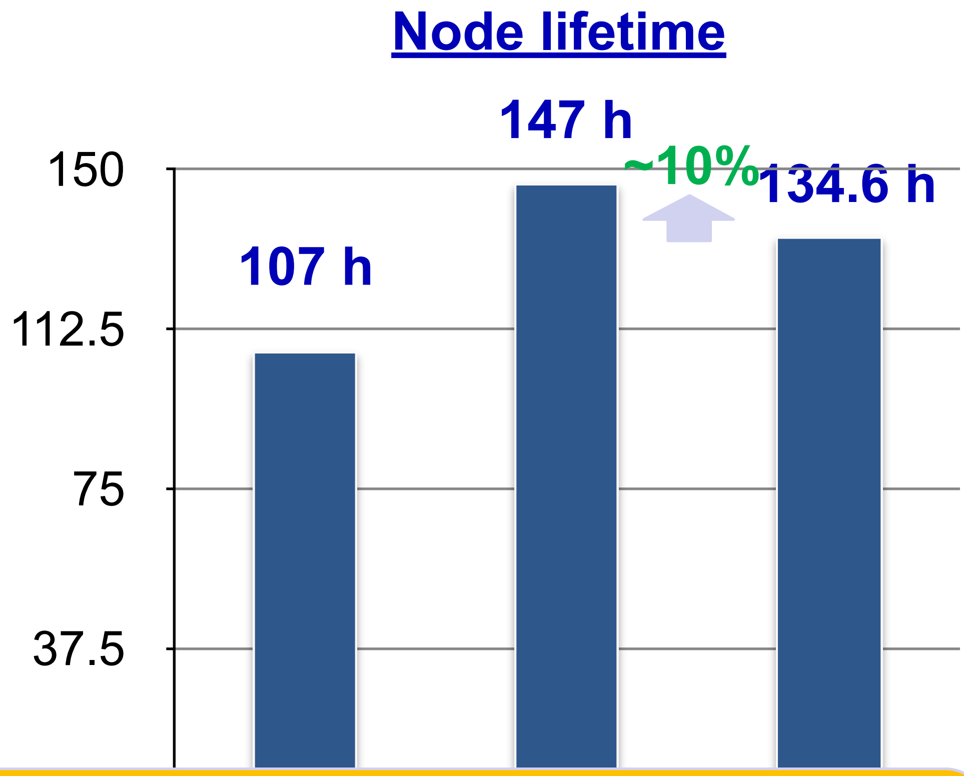


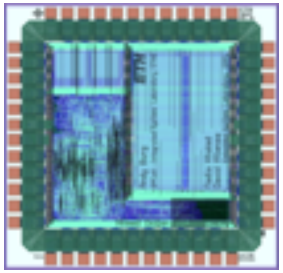


Limited gains because the used generic microcontroller is not optimized for ultra-low power **DSP and CS-based operations in biological signals**

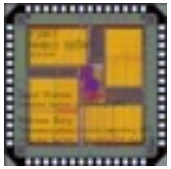
Simplicity is the key: A new generation of ultra-low-power processing cores for WBSNs

- FIRAT/TamaRISC: Inspired on PIC24
  - 16-bit RISC, simple 3-stage pipeline
  - Drastically reduced to 25 types of instructions (added CS execution support)
  - 1 cycle/inst., Immediate branch, full data bypass
  - Minimal ALU: ADD, SUB, AND, OR, XOR, Shift, Mult.

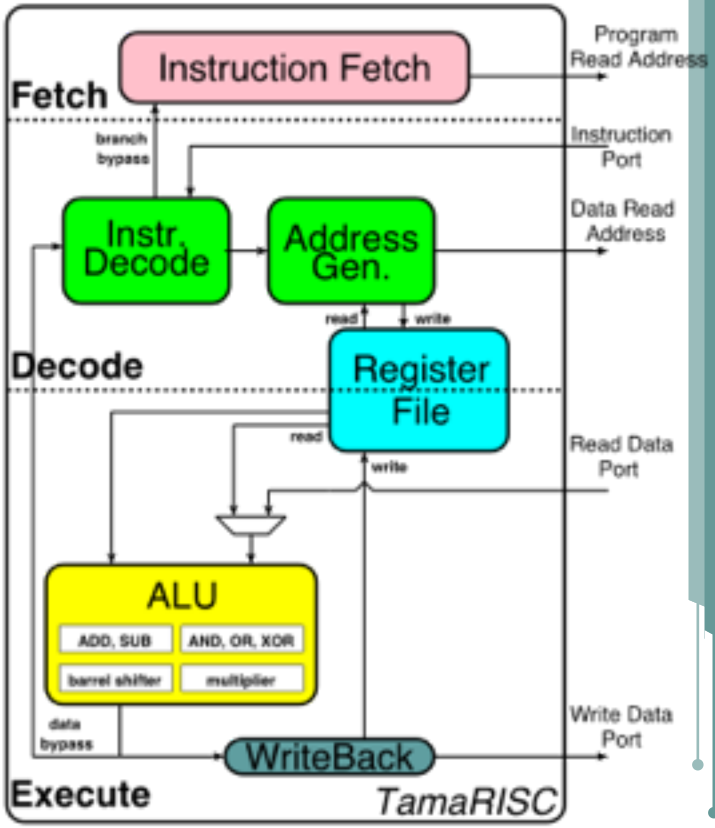
- Minimal area/power for biosignals processing
  - Less than 5% of an embedded platform (< 10 kGE)
  - Low-power computing: ~10 MHz (180MHz@1V)



Dicle (umcL 180nm)



Firat (umcL 90nm)



[Dogan et al., DATE 2012]

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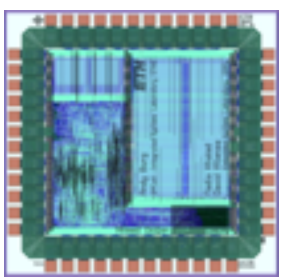

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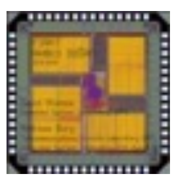
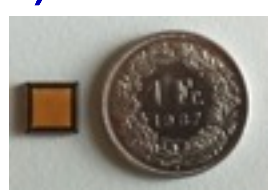
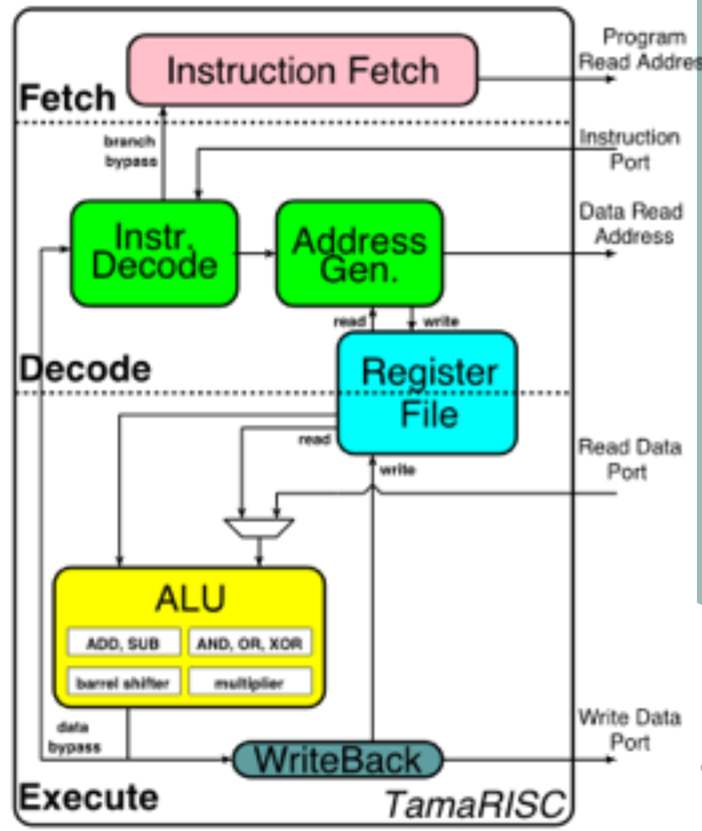


Firat (umcL 90nm)



Firat ASIC vs. 1chf coin



[Dogan et al., DATE 2012]

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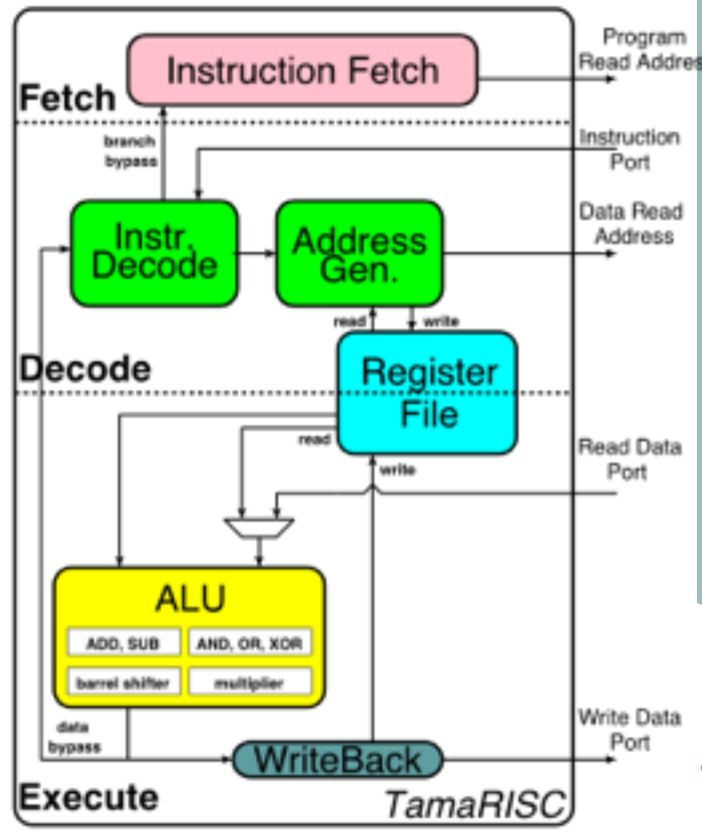
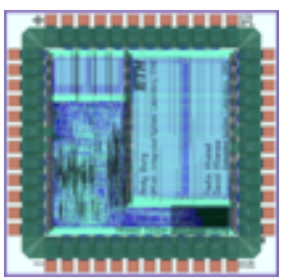


[Dogan et al., DATE 2012]



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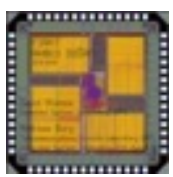
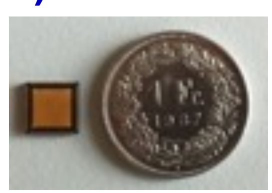


Firat (umcL 90nm)

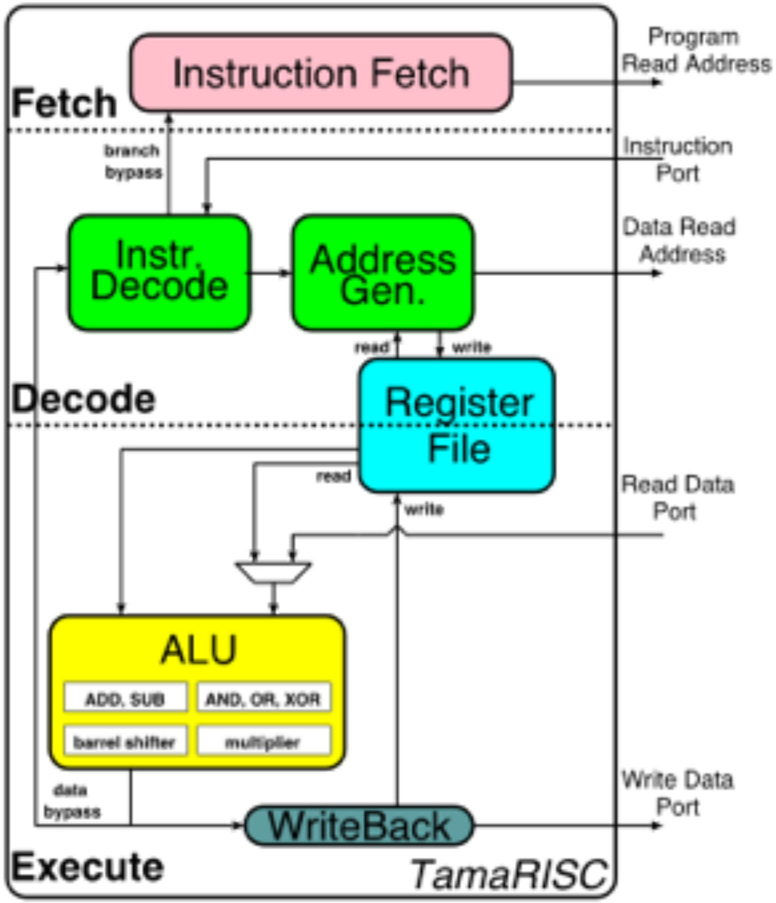


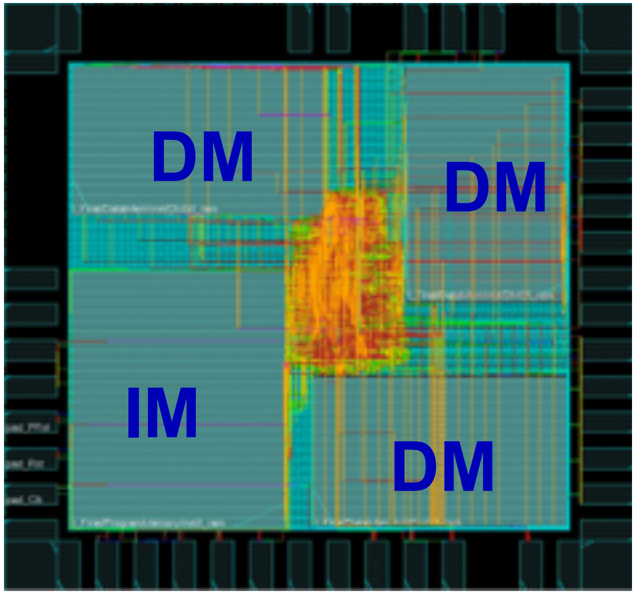
Firat ASIC vs. 1chf coin

… And on a finger tip!

Simplicity is the key: TamaRISC processing core and memories

- Specialized 16-bit RISC for biosignals
  - But **memories are key:** 50% energy





[Dogan et al., DATE 2012]

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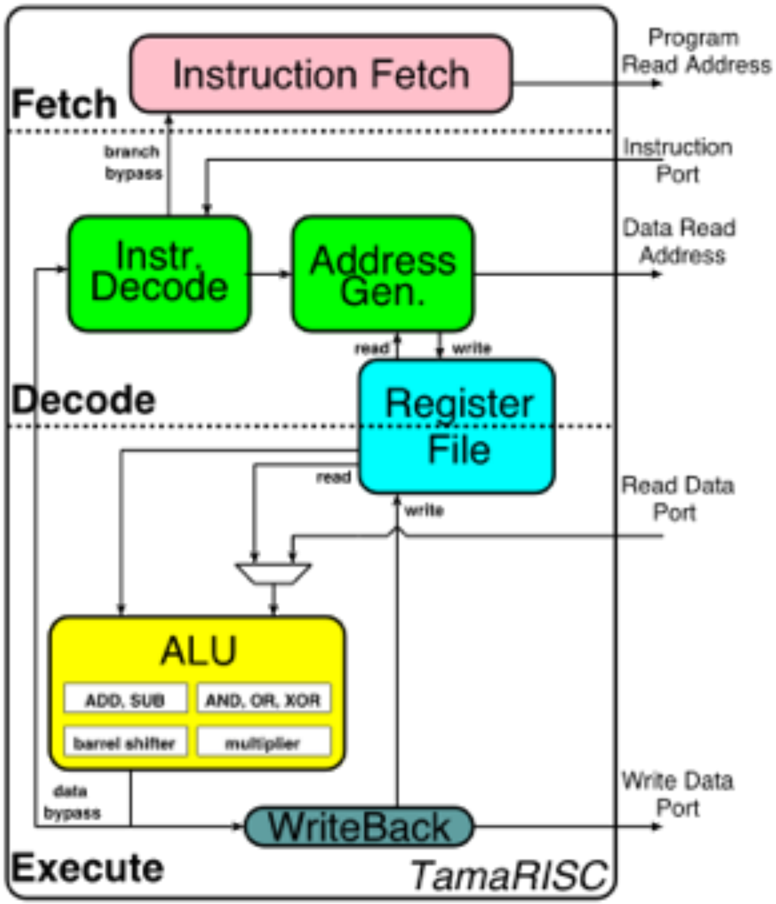
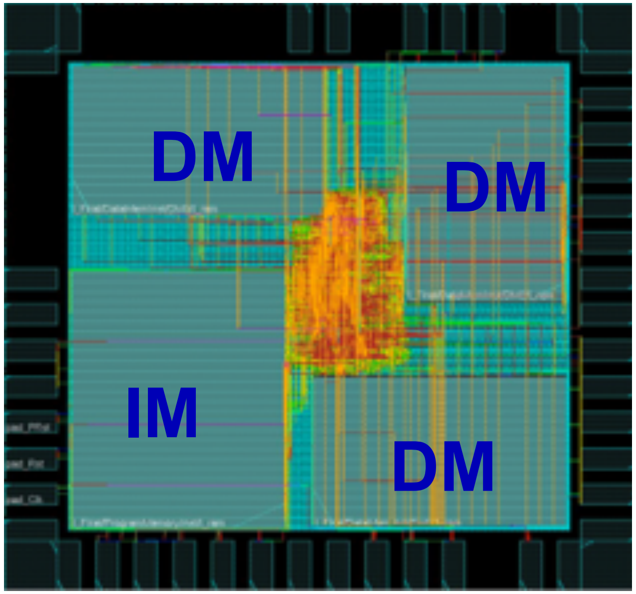


[Dogan et al., DATE 2012]



- Low-voltage multi-banked memories
  - 32-kB instruction memory (IM)
  - 36-kByte data memory (DM)

[Dogan et al., DATE 2013]

TamaRISC: Experimental results

	Number of Clock Cycles(*)		
	FIRAT	TamaRISC	MSP430
Filtering-DWT	1.85M K	1.81M	4.7M
Compression	114K	90K	800K

(*) 1-package compression (512 samples)

TamaRISC only 38% of MSP430 cycles due to architecture specialization and low voltage operation

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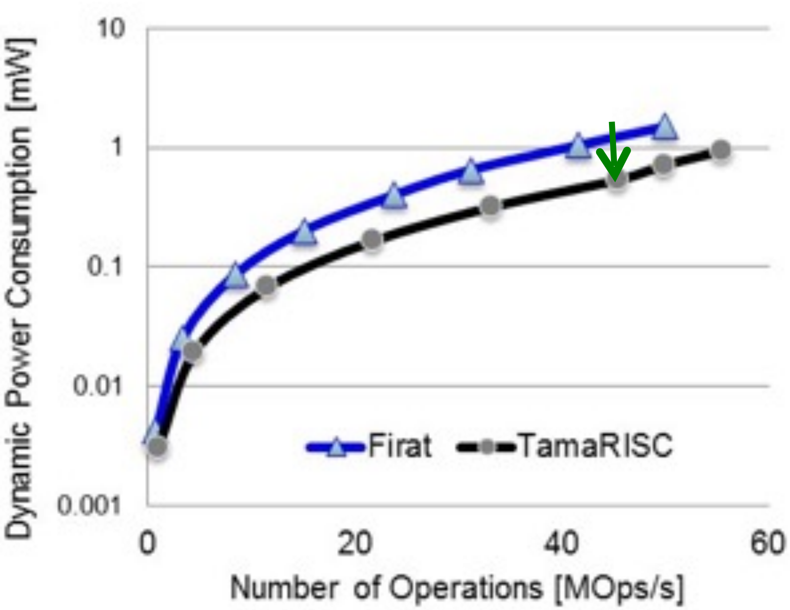

TamaRISC vs Firat: Faster and 30% extra power savings due to full data bypass, CS support and low-power encoding

	Energy per Ops @ 1.0 V	Technology
TamaRISC	12.1 pJ	90 nm
16-bit [Kwong,2011]	> 47 pJ	130 nm
32-bit [Ickes,2011]	19.7 pJ-27 pJ	65 nm

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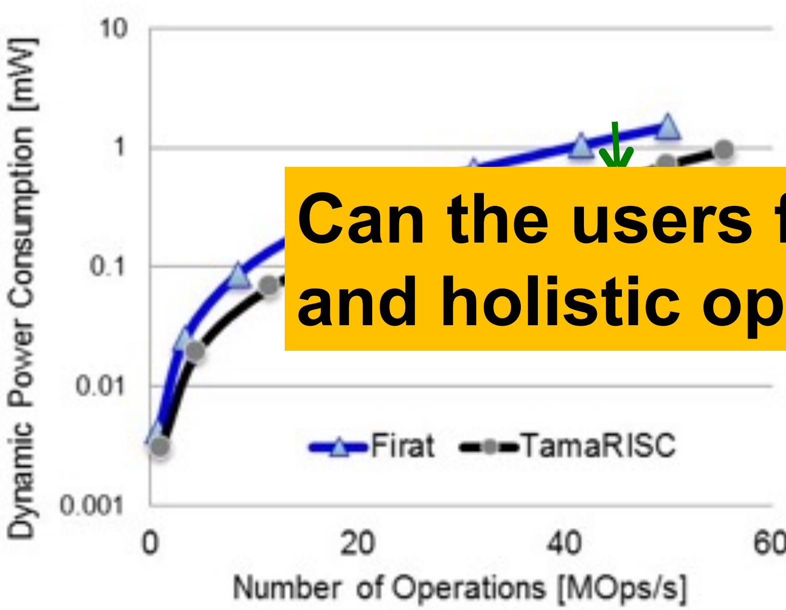

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Can the users finally see the benefit of CS and holistic optimization at system-level?

		ogy
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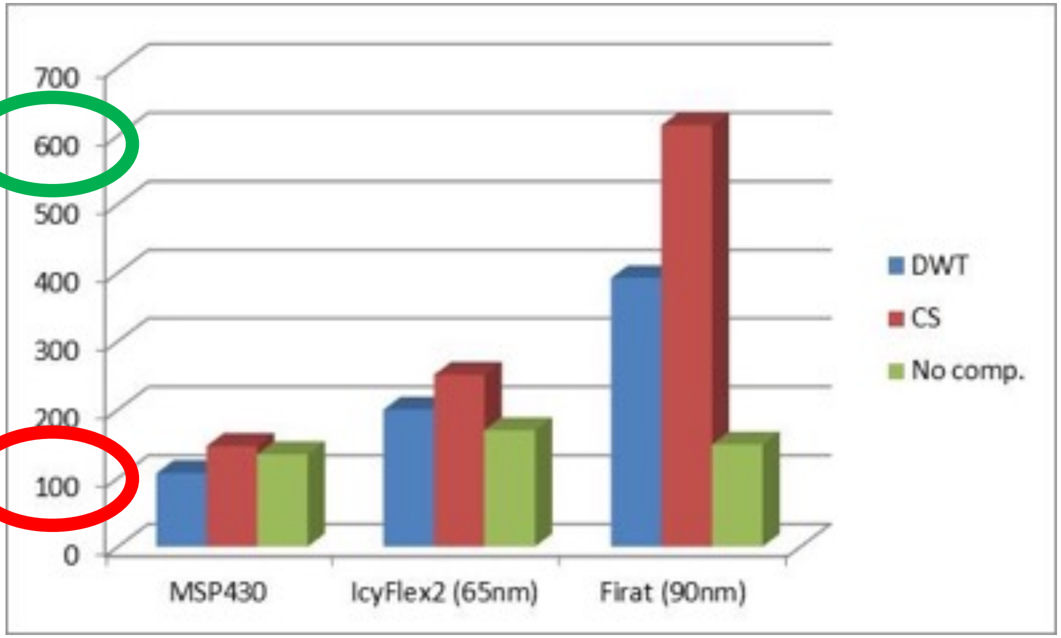
32-bit [Ickes,2011]	19.7 pJ-27 pJ	65 nm

CS and biosignals algorithms analysis show true advantages on ultra-low-power (ULP) processors

Lifetime (in hours)



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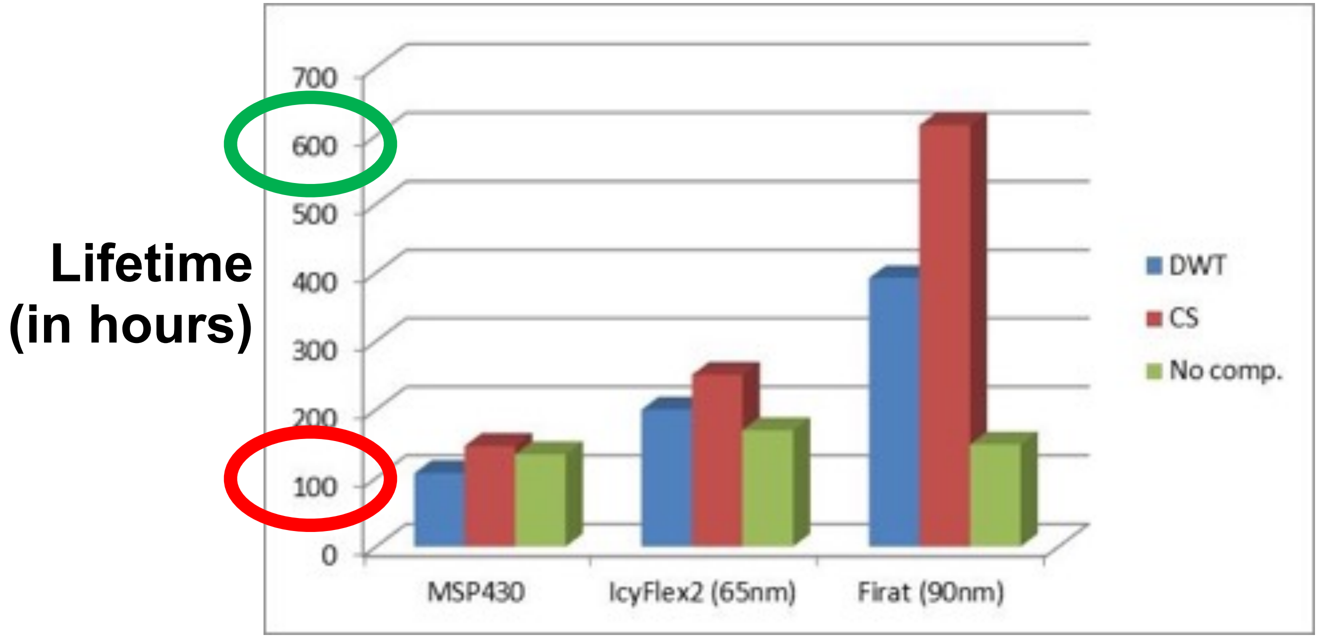


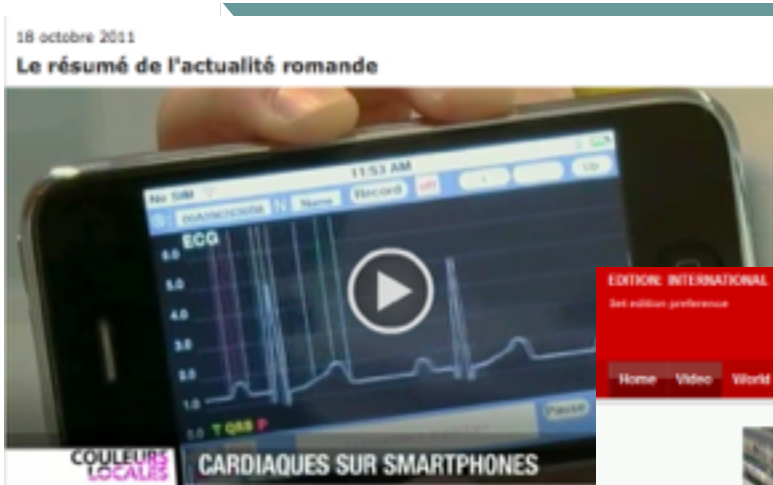
SmartCardia

- Feasible to develop long-lasting smart WBSN nodes that interact with smartphones
  - Adapts at run-time to patient's heart
  - Automatic detection of arrhythmias
  - Real-time notification to doctors

CS and biosignals algorithms analysis show true advantages on ultra-low-power (ULP) processors

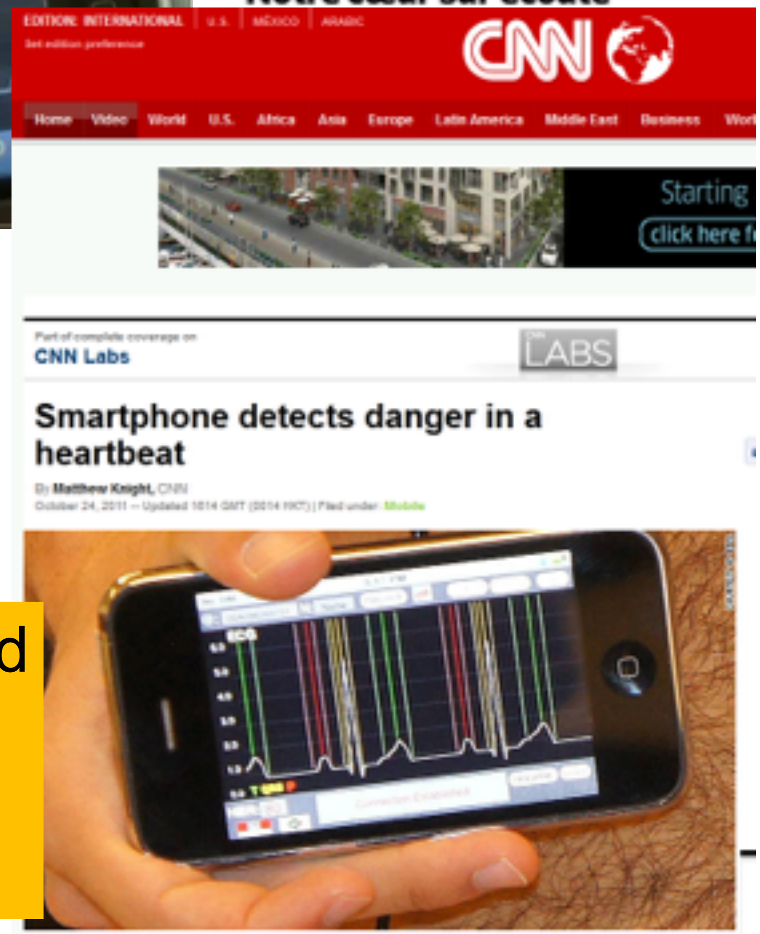
See video at: http://www.smartcardia.com

Smart ULP WBSN designs can reach resonance in the media, but also impact in medical community!



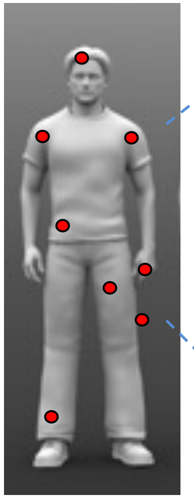

Date: 19.10.2011
LE TEMPS
Santé
Notre cœur sur écoute

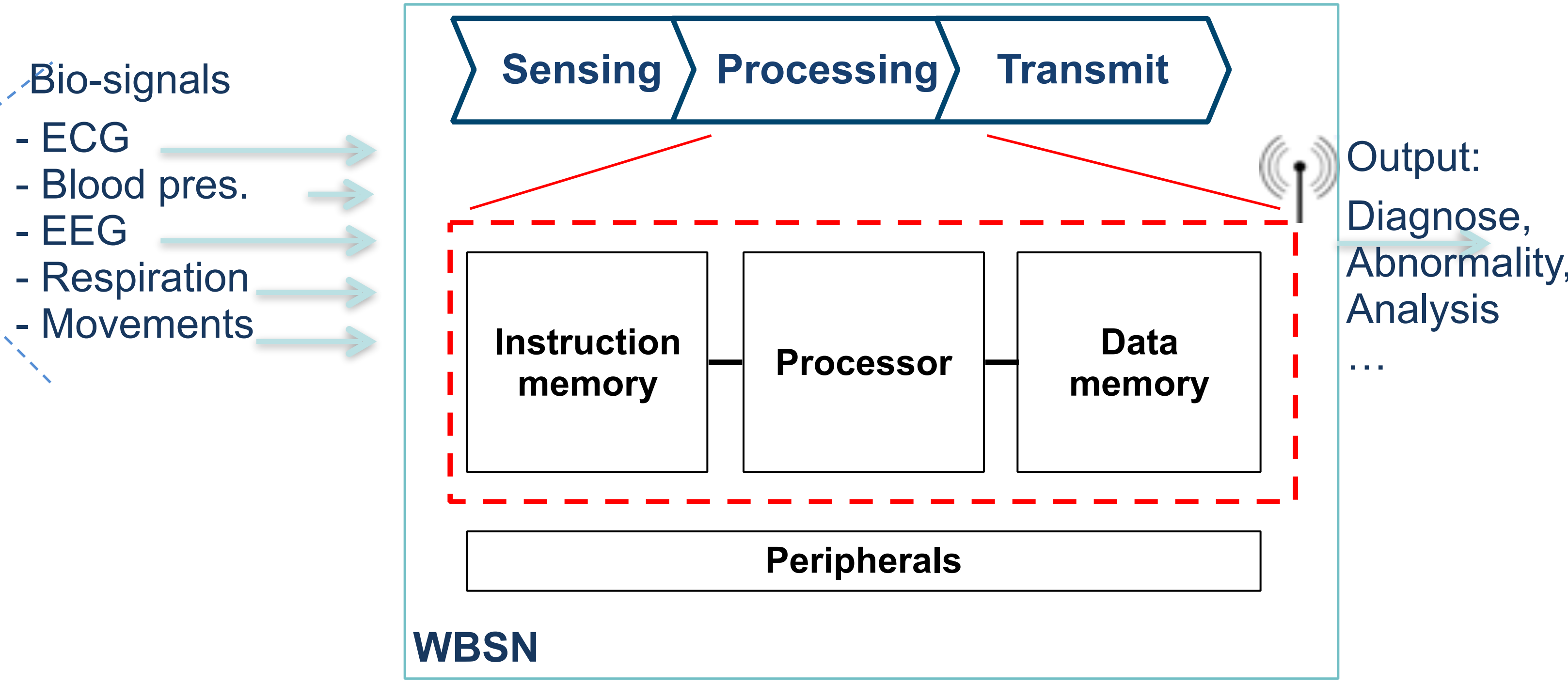

Date: 19.10.2011
Blick
Ein SMS vom Herz
Lausanne – Diagnose: Herzinfarkt. Der häufigsten Todesursache der Welt wird der Kampf angesagt, und zwar mit Schweizer Technik. Forscher der ETH Lausanne haben ein Gerät entwickelt, das den Herzrhythmus konstant überwachen kann. Falls eine Rhythmusstörung auftritt, **sendet das Gerät an Patient und Arzt per SMS oder E-Mail eine Warnung.** «Das System liefert sehr präzise Daten und verfügt über einen leistungsfähigen Akku mit einer Laufzeit von drei bis vier Wochen», sagt Forscher David Atienza.


EDITION: INTERNATIONAL
CNN
Home Video World U.S. Africa Asia Europe Latin America Middle East Business
Part of complete coverage on
CNN Labs
Smartphone detects danger in a heartbeat
By Matthew Knight, CNN

Non-intrusive, light and can reduce visits by 50-60% for patients (4-week test)

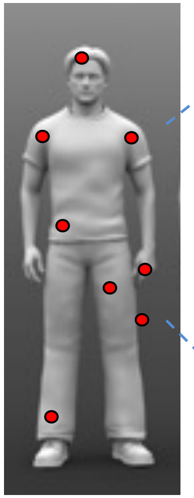
Next-Generation: “Really Smart” (or just Smarter) WBSN for Healthcare



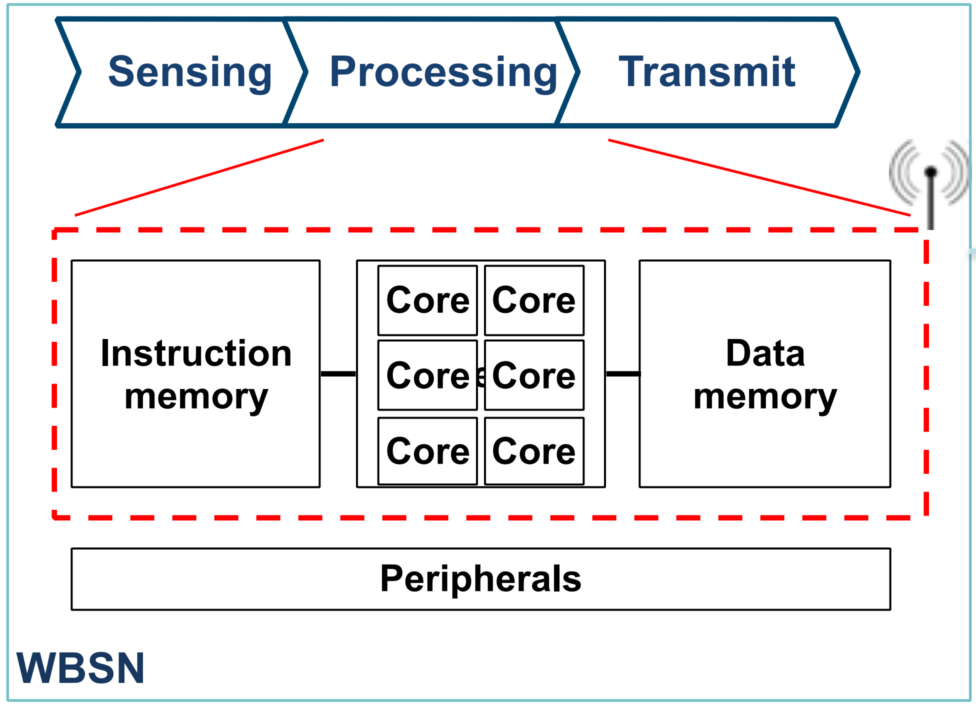


CAN WE DO BETTER?

Next-Generation: "Really Smart" (or just Smarter) WBSN for Healthcare



Bio-signals
- ECG
- Blood pres.
- EEG
- Respiration
- Movements



Output:
Diagnose,
Abnormality,
Analysis
…

CAN WE DO BETTER?

SW
- **Selective DSP (Classification)**
- **Multi-lead Compression**

HW
- **Ultra-low Power (ULP) architectures**
- **Hybrid CS-based front end design**

Let's exploit BIG DATA!

Outline

Software

- On-node compression
  - **Selective advanced ECG analysis**
  - Multi-lead compression
  - Robust Compressed Sensing

Hardware

- CS-based Analog to Information
  - ECG ultra-low-power front-end design

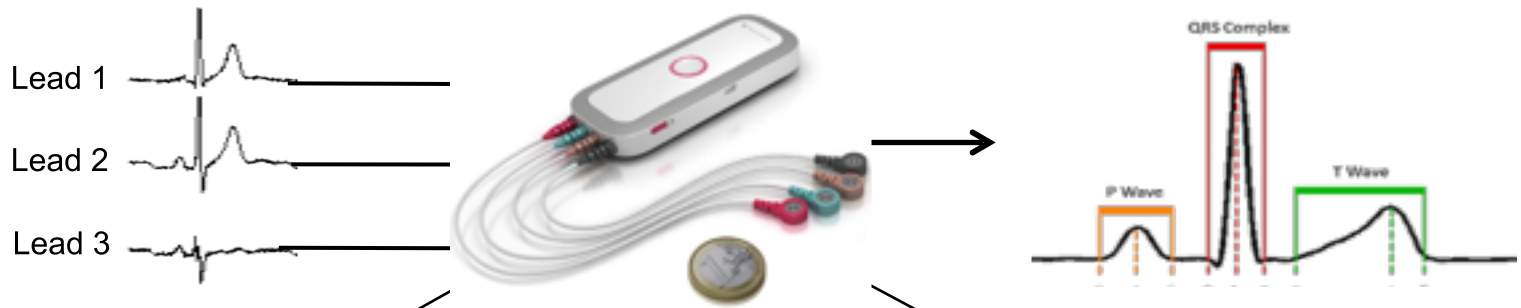
Selective advanced ECG analysis

Advanced DSP → **Delineation**

WBSN Example:
- TamaRISC µC
  - 8 MHz
  - 16-bit
  - 128 KB
  - Flash
- CC240 radio
  - Zigbee
  - Bluetooth
- 480 mAh Battery

→1200h running

Selective advanced ECG analysis



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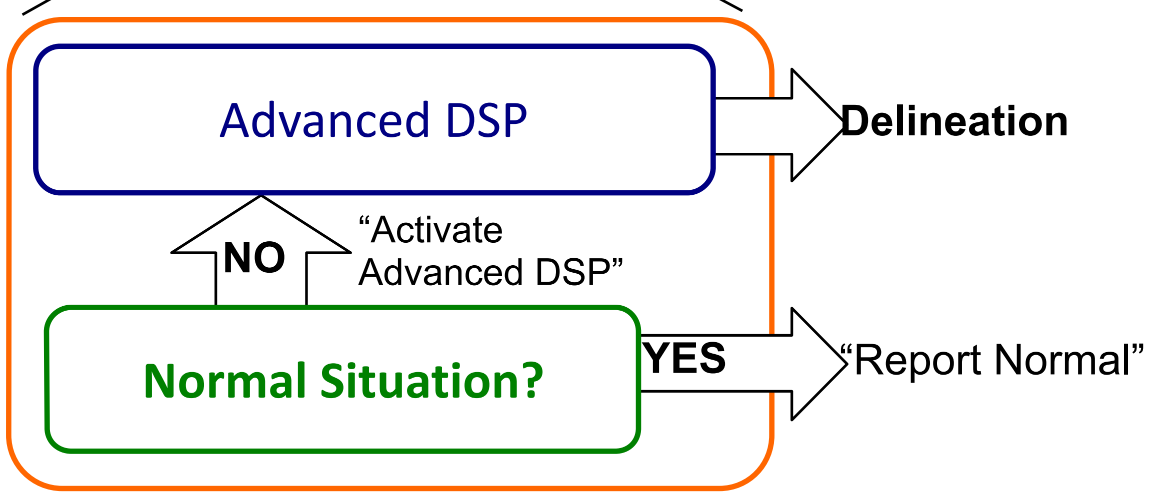
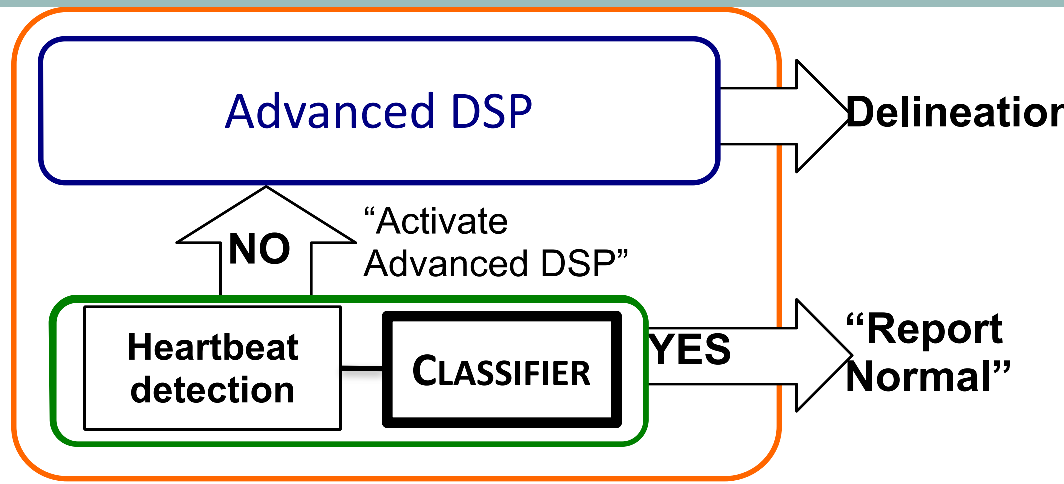


<u>Possible Selective Activation?</u>

Classification of Heartbeats

- Normal condition
  - Normal heartbeat morphology
- <u>Classif. heartbeats</u>
  - Problem dimensionality
  - Very complex existing algorithms



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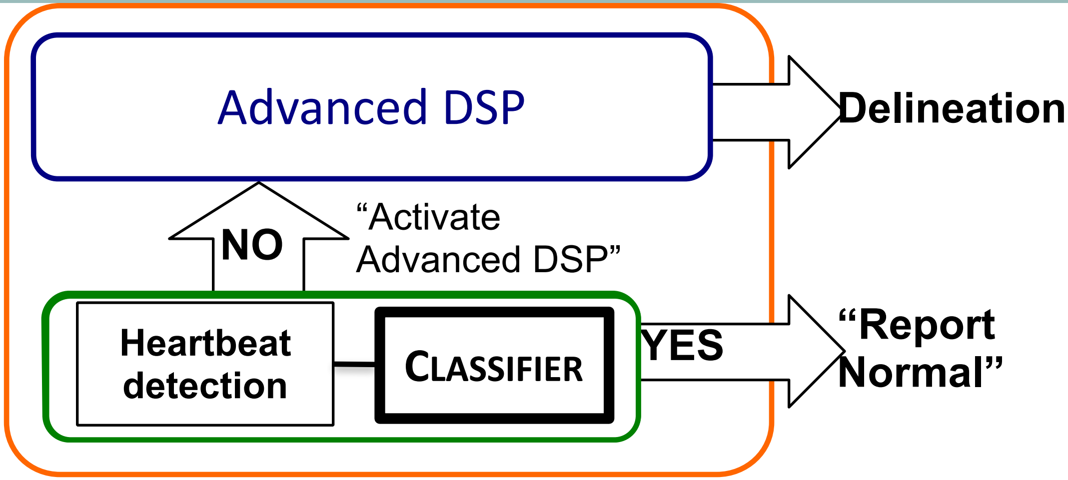
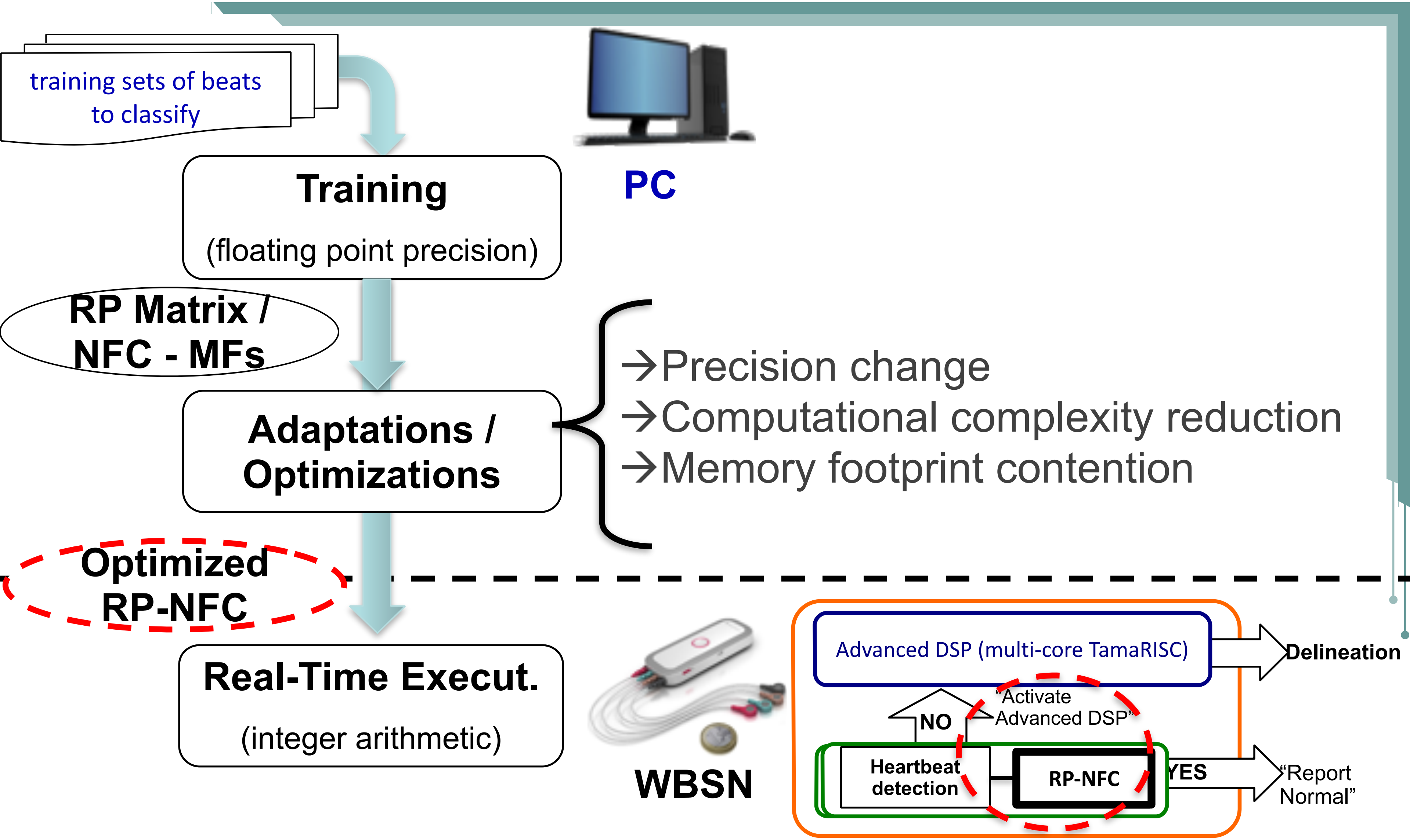


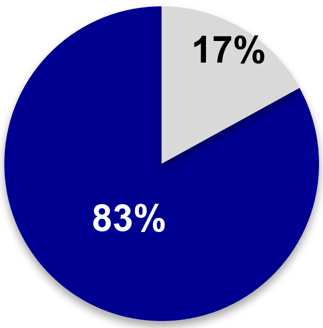
Light-weight embedded heartbeat classifier

1. Random Projection (RP) dimensionality reduction
2. Embedded Neuro-Fuzzy classifier (NFC)

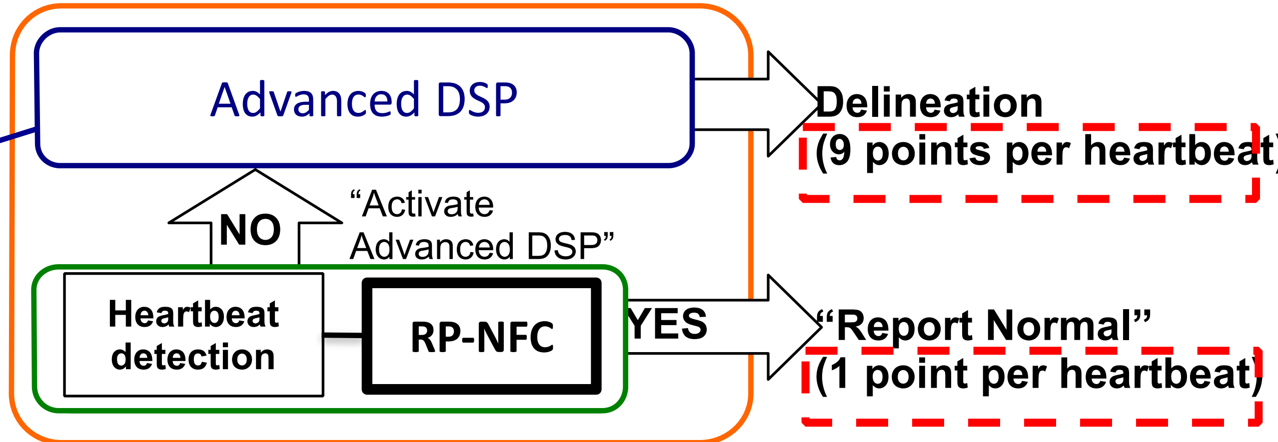
Proposed framework for next-generation WBSN designs



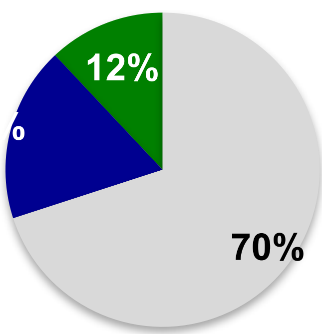
Initial Case study: Smarter ECG Monitor



Typical ECG Monitor



Duty Cycle
- Advanced DSP
- Extension
- Idle Time



Smarter ECG Monitor

- Duty cycle reduction of 65% for MIT-BIH DB
- Transmission or storage reduction of 68%
- In a real test with multi-core WBSN node
  → Energy savings of 23%

Up to 61.5 days of operation (~1476 hours), finally we got our ULP WBSN!

Outline

Software

- On-node compression
  - Single-lead compression
  - **Multi-lead compression**
  - Robust Compressed Sensing

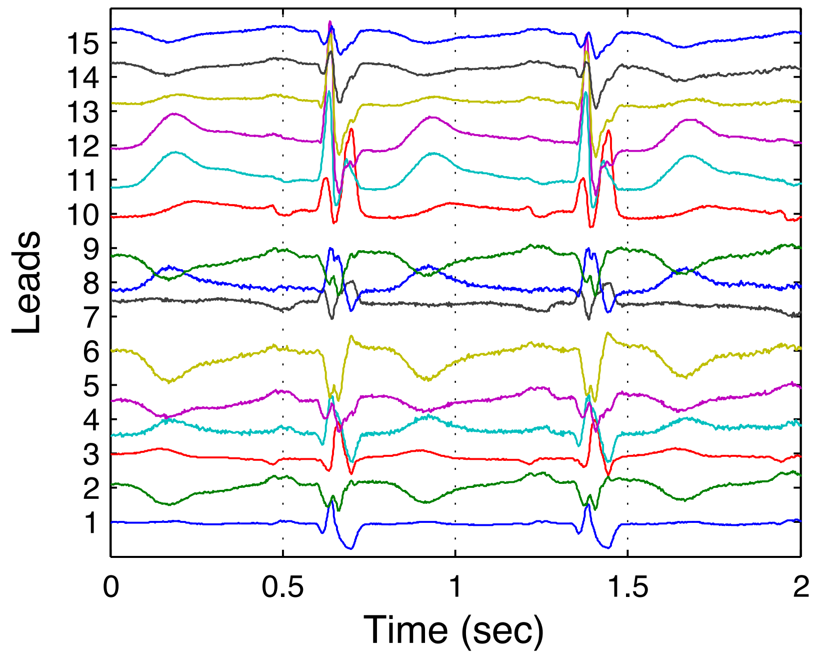
Hardware

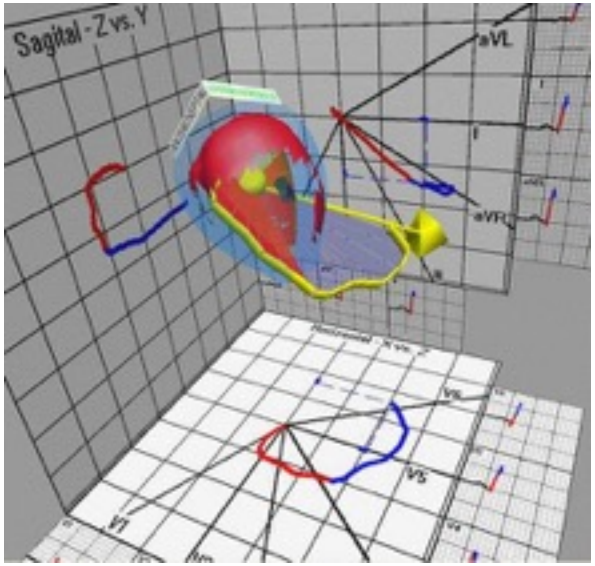
- CS-based Analog to Information
  - ECG ultra-low-power front-end design

Multi-lead Compression

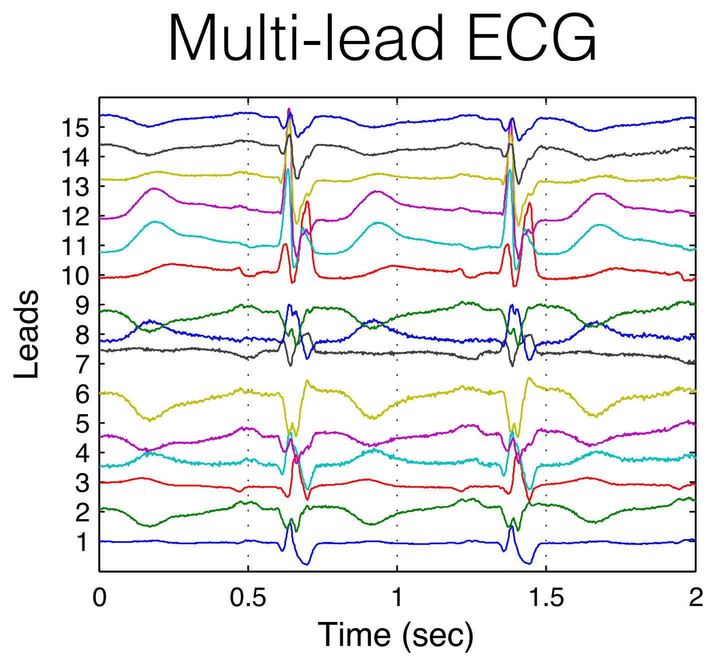
- Doctors need multi-lead ECG signals

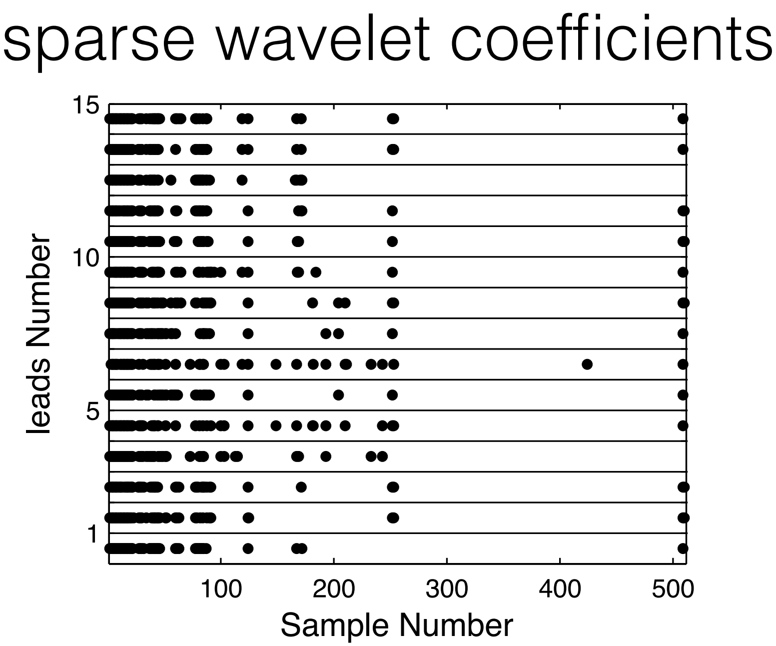
  - ECG leads are different projections of a single multi-diminutional source.





Joint Sparsity Structure



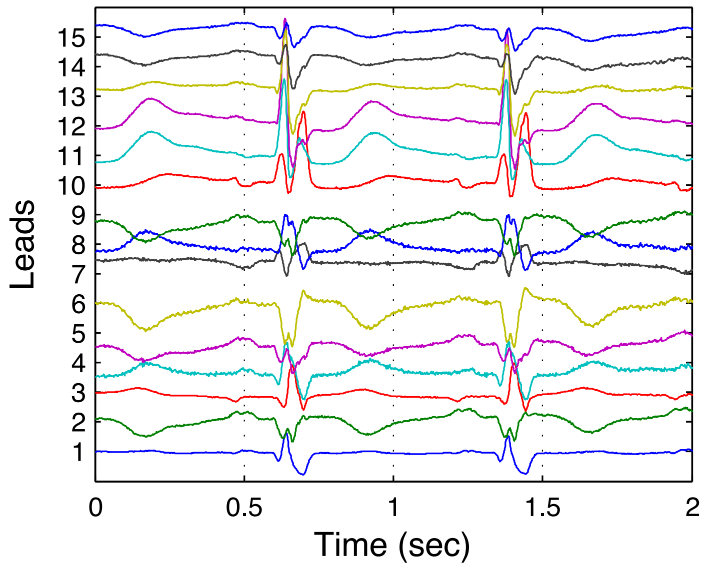


- Strong similarity exist between support of sparse representation among leads.
- Required measurements in normal CS $m = \mathcal{O}(s \log \frac{n}{s})$

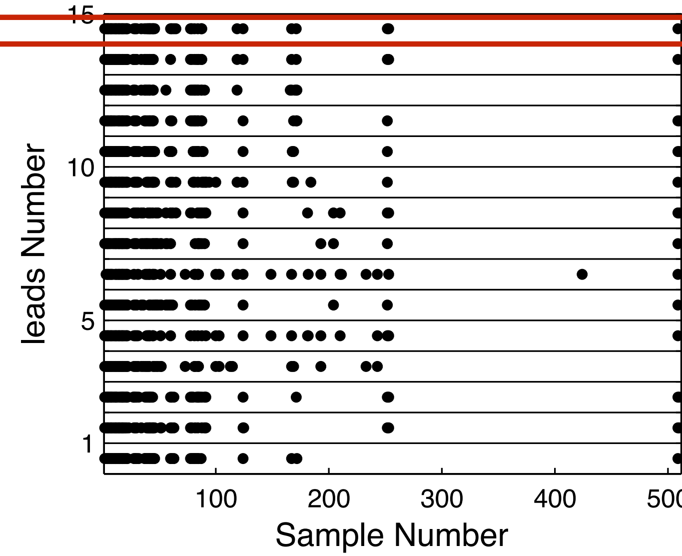
To embed the location of non-zeros

Joint Sparsity Structure

Multi-lead ECG

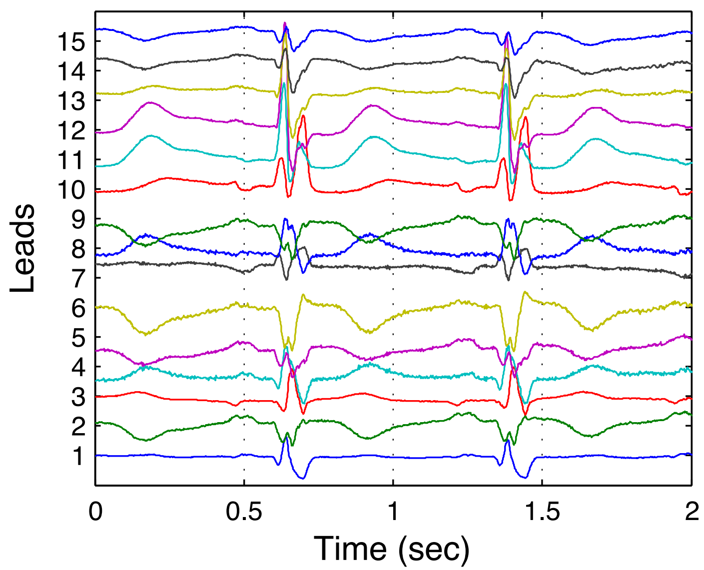


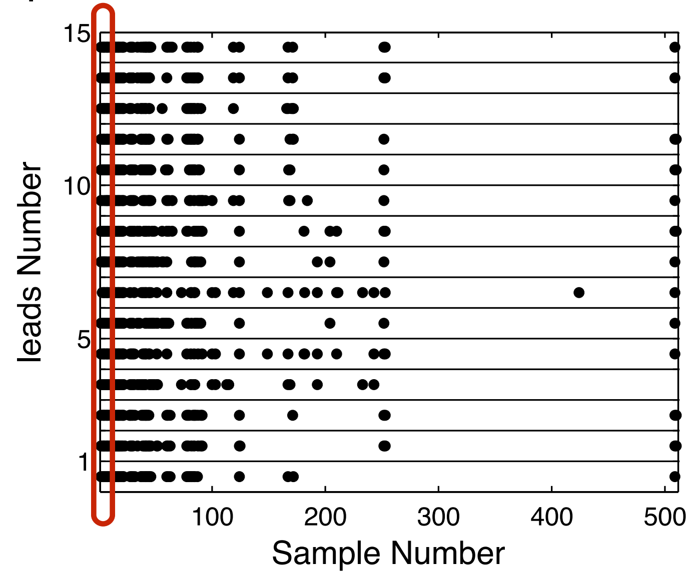
sparse wavelet coefficients



CS: $$\min_{\hat{\alpha}\in\mathbb{R}^N} \left\|\hat{\mathbf{A}}\right\|_1 \quad \text{subject to:} \quad \left\|\Phi\Psi\hat{\mathbf{A}} - y\right\|_2 \leq \sigma$$

Joint Sparsity Structure

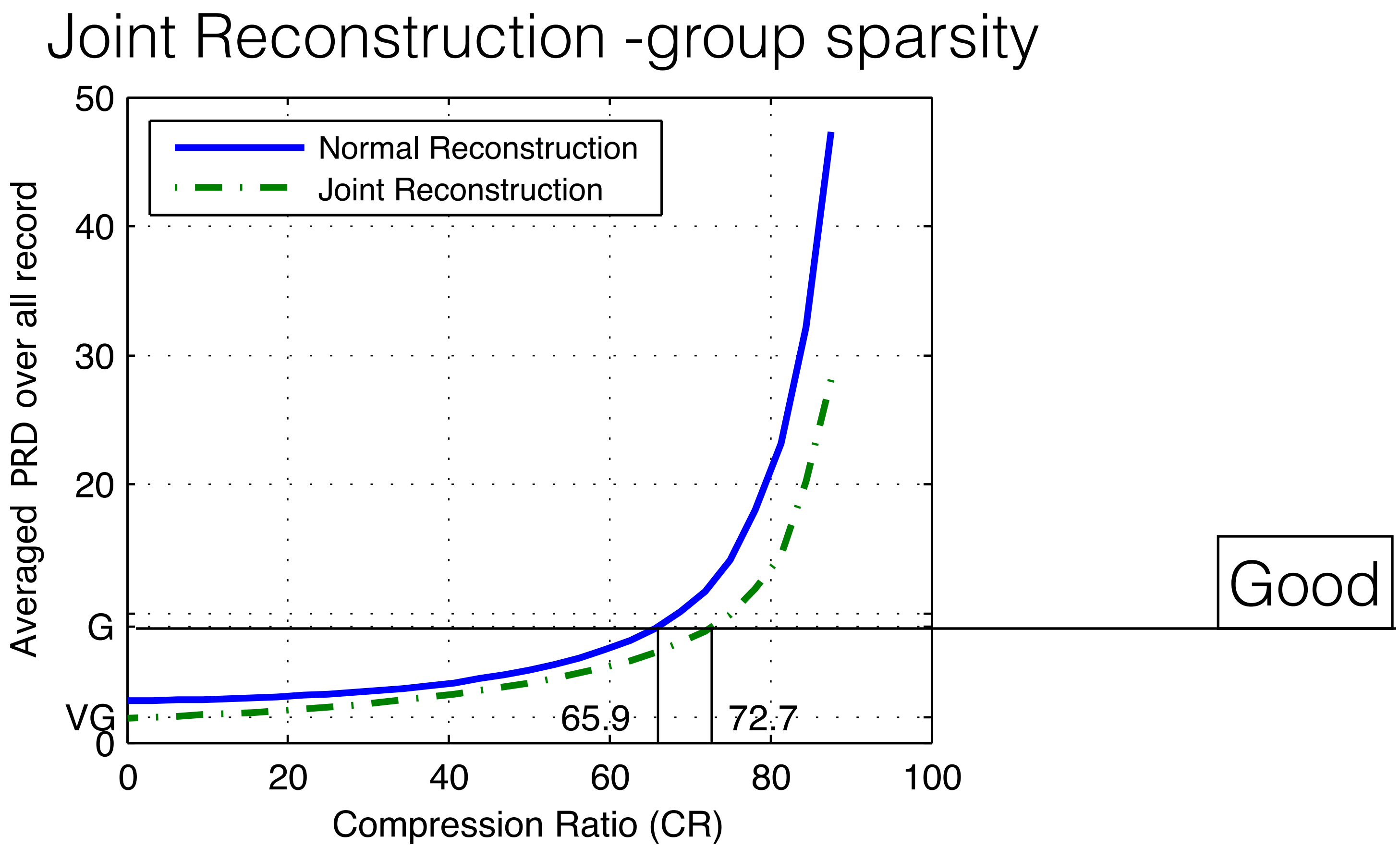




CS: $\min_{\hat{\alpha}\in\mathbb{R}^N} \left\|\hat{\mathbf{A}}\right\|_1$ subject to: $\left\|\Phi\Psi\hat{\mathbf{A}} - y\right\|_2 \leq \sigma$

Joint comp: $\min_{\hat{\alpha}\in\mathbb{R}^N} \left\|\hat{\mathbf{A}}\right\|_{1,2}$ subject to: $\left\|\Phi\Psi\hat{\mathbf{A}} - y\right\|_2 \leq \sigma$

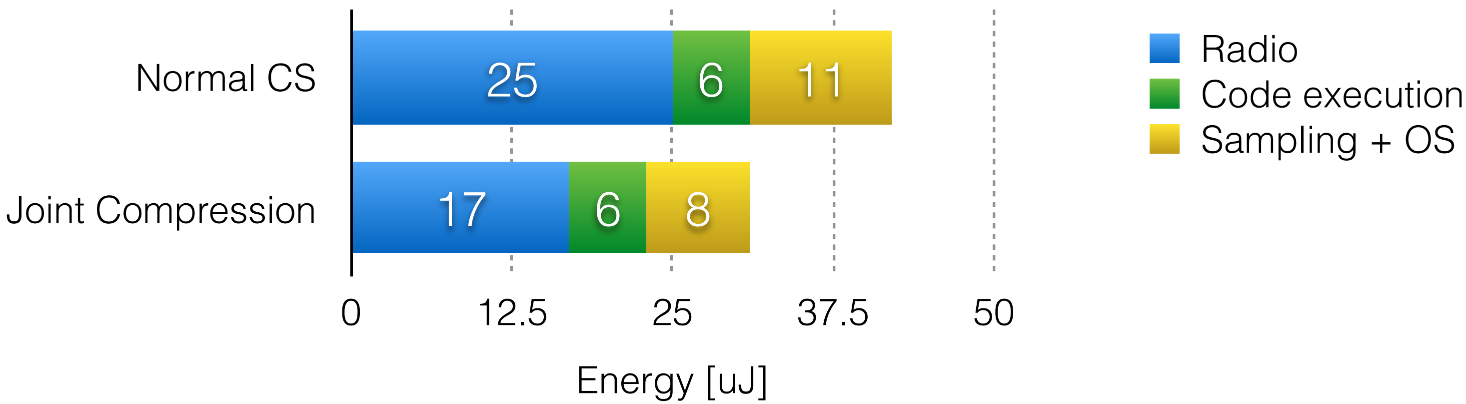
Joint Compression: Results



- **7%** improvement of Compression ratio

Power Consumption breakdown

- Power consumption comparison



- **26%** node lifetime extension on top of normal CS (Shimmer Platform)

Outline

Software

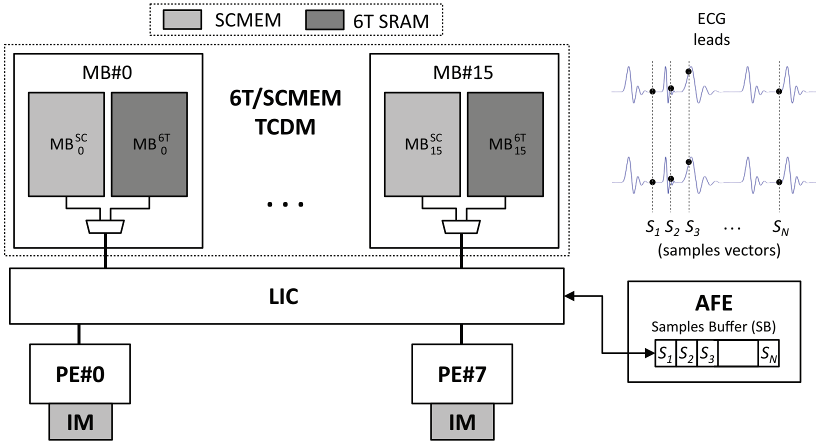
- On-node compression
  - Single-lead compression
  - Multi-lead compression
  - **Robust Compressed Sensing**

Hardware

- CS-based Analog to Information
  - ECG ultra-low-power front-end design

Hybrid Memory on a Multi-core Processor

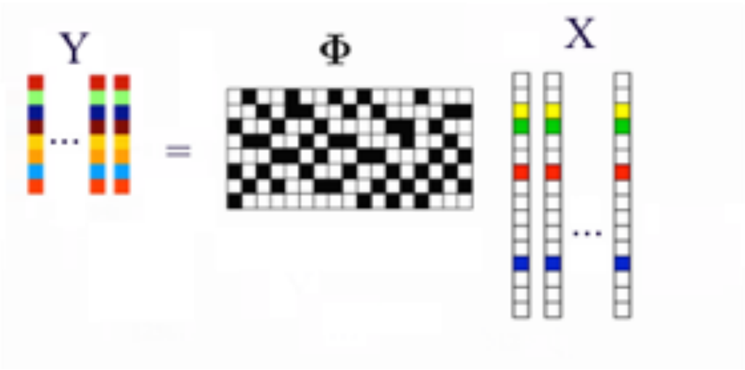
- Use of reliable Standard Cell (SC) Memories (SCMEM) allows scaling to lower supple voltage, but in cost of large area penalties.
- Use of 6 Transistor SRAM (6T) cell memories are not reliable in supply voltage scaling.
- Ultra-low power multi-core architecture for multi-channel bio-signal processing.
- Hybrid memory architecture with 6T SRAM and SCMEM working on a aggressive voltage scaling.



Architecture designed by university of Bologna

Robust Compressed Sensing

Sensing Matrix is stored in 6TMEMs



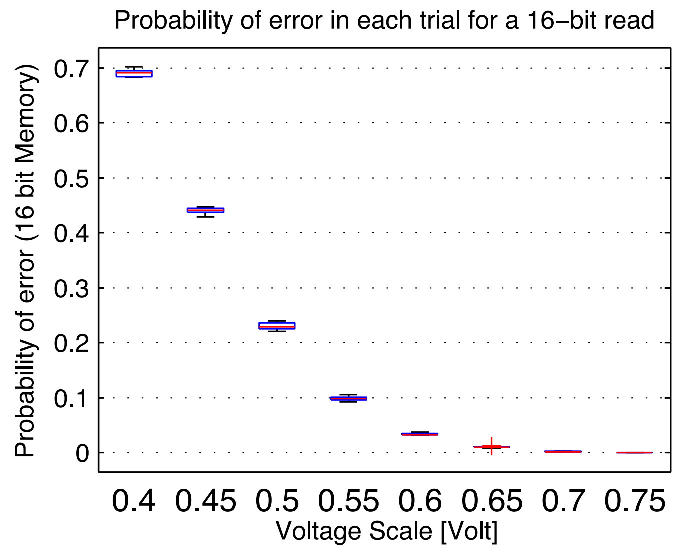
Robust Compressed Sensing

Sensing Matrix is stored in 6TMEMs

Joint comp:

$$\mathbf{Y} = \Phi\mathbf{X} = \Phi\Psi\mathbf{A}$$

$$\min_{\hat{\alpha}\in\mathbb{R}^N} \left\|\hat{\mathbf{A}}\right\|_{1,2} \quad \text{subject to:} \quad \left\|\Phi\Psi\hat{\mathbf{A}} - \mathrm{Y}\right\|_2 \leq \sigma$$



Robust Compressed Sensing

Sensing Matrix is stored in 6TMEMs

Joint comp:

$$\mathbf{Y} = \Phi\mathbf{X} = \Phi\Psi\mathbf{A}$$

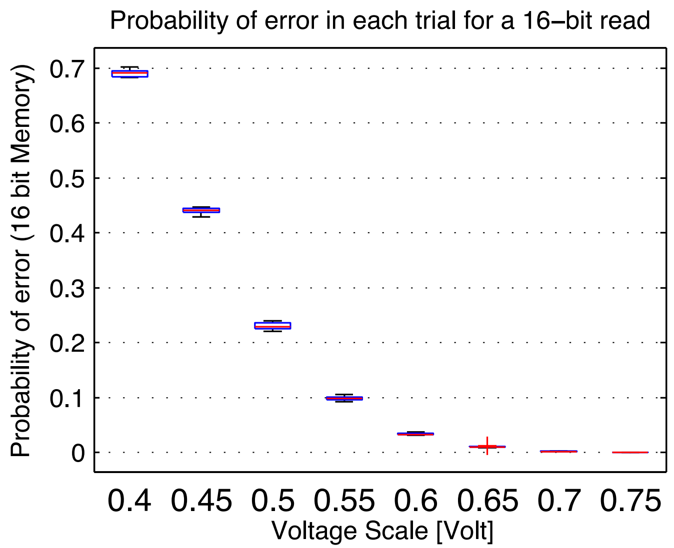
$$\min_{\hat{\alpha}\in\mathbb{R}^N} \left\|\hat{\mathbf{A}}\right\|_{1,2} \quad \text{subject to:} \quad \left\|\Phi\Psi\hat{\mathbf{A}} - \mathrm{Y}\right\|_2 \leq \sigma$$

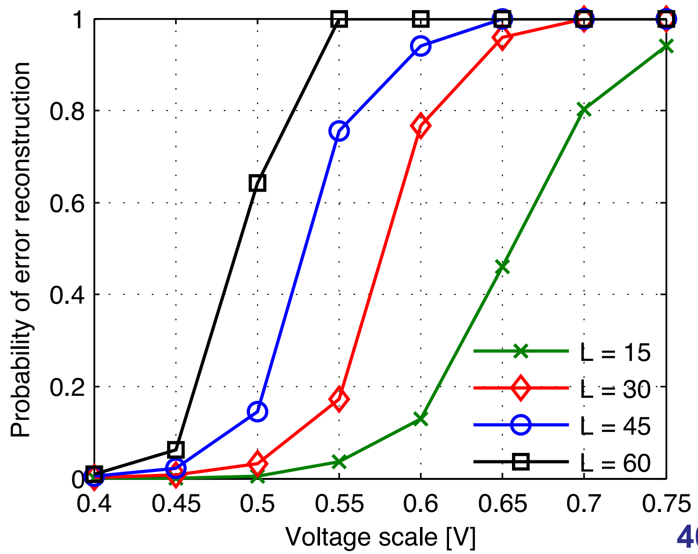
Joint comp with Error:

$$\mathbf{Y} = (\Phi + \mathbf{E})\mathbf{X} = (\Phi + \mathbf{E})\Psi\mathbf{A}$$

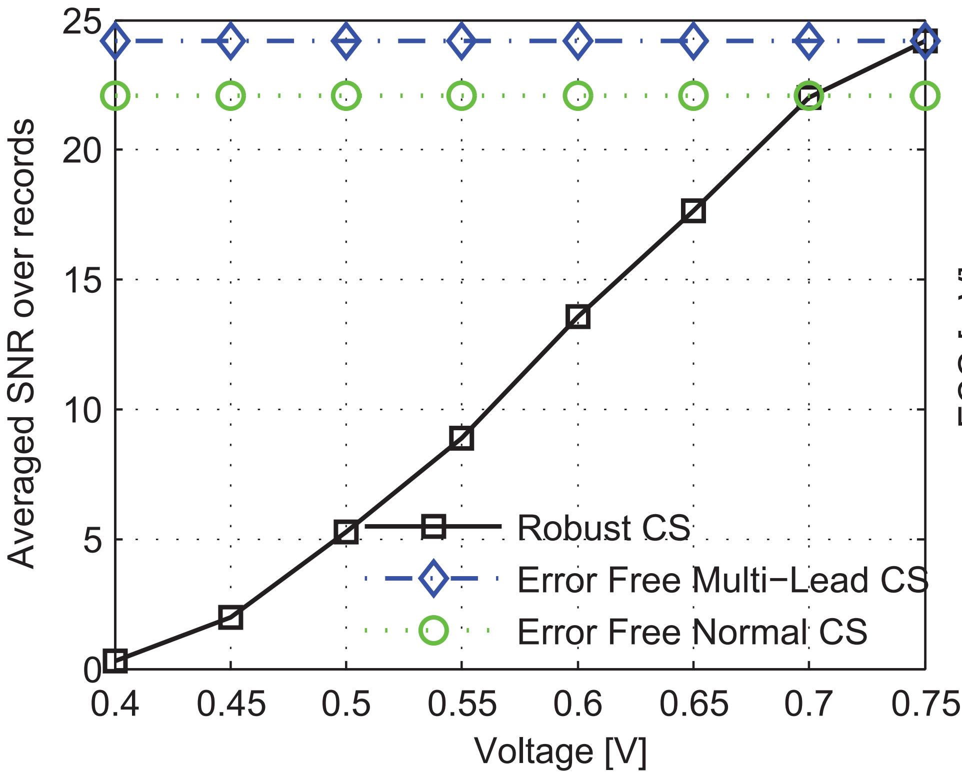
Robust Compressed Sensing

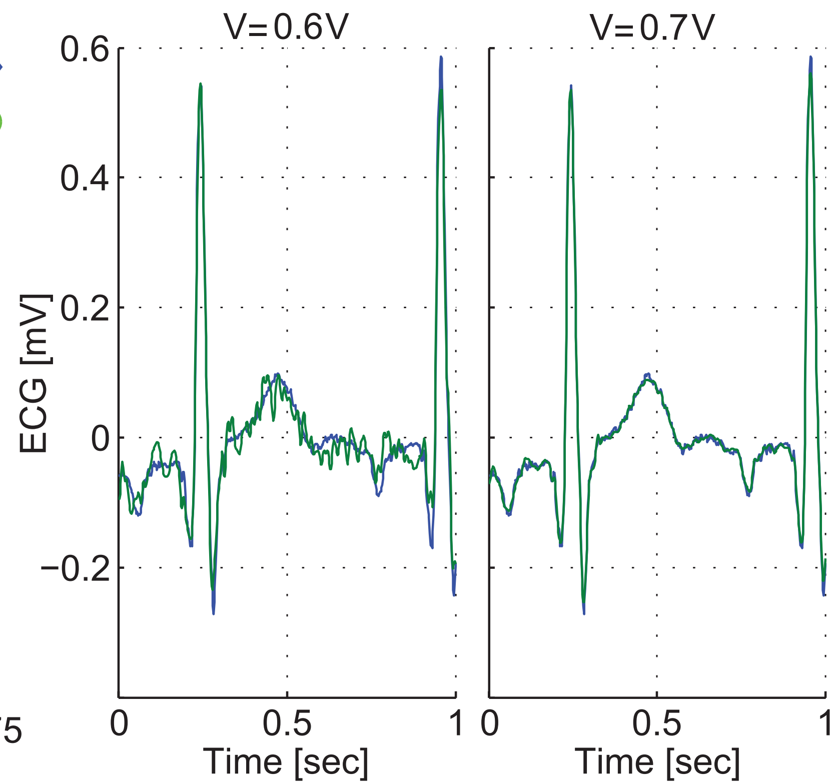
$$\min_{\hat{\mathbf{A}},\hat{\mathbf{E}}} \left\|\hat{\mathbf{A}}\right\|_{1,2} + \lambda\left\|\hat{\mathbf{E}}\right\|_1 \quad \text{s.t:} \quad \left\|(\Phi + \hat{\mathbf{E}})\Psi\hat{\mathbf{A}} - \mathrm{Y}\right\|_2 \leq \sigma$$





Robust Compressed Sensing





Design reach to **60%** reduction in Power consumption with a 13% area overhead

Outline

Software

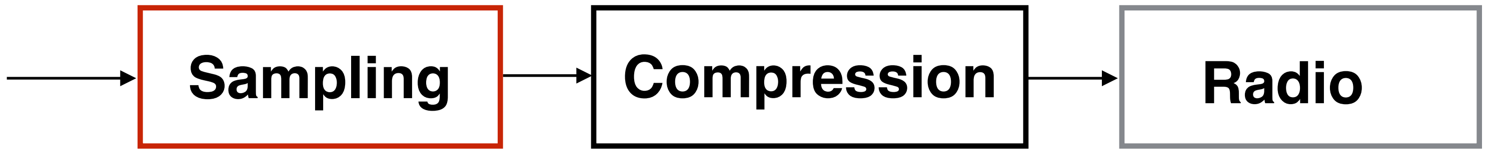
- On-node compression
  - Single-lead compression
  - Multi-lead compression
  - Robust Compressed Sensing

Hardware

- **CS-based Analog to Information**
  - ECG ultra-low-power front-end design

CS-based A2I

- Why analog implementation?

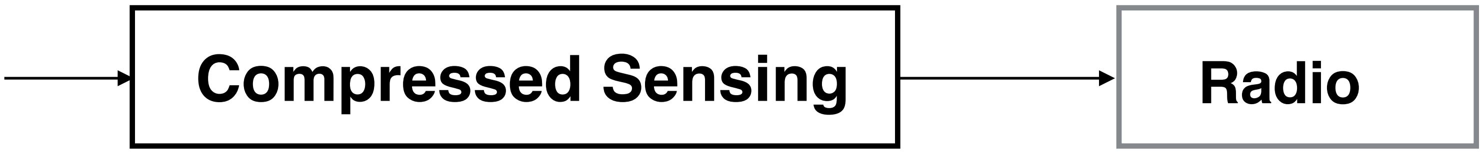


CS-based A2I

- Why analog implementation?

CS-based A2I

- Why analog implementation?



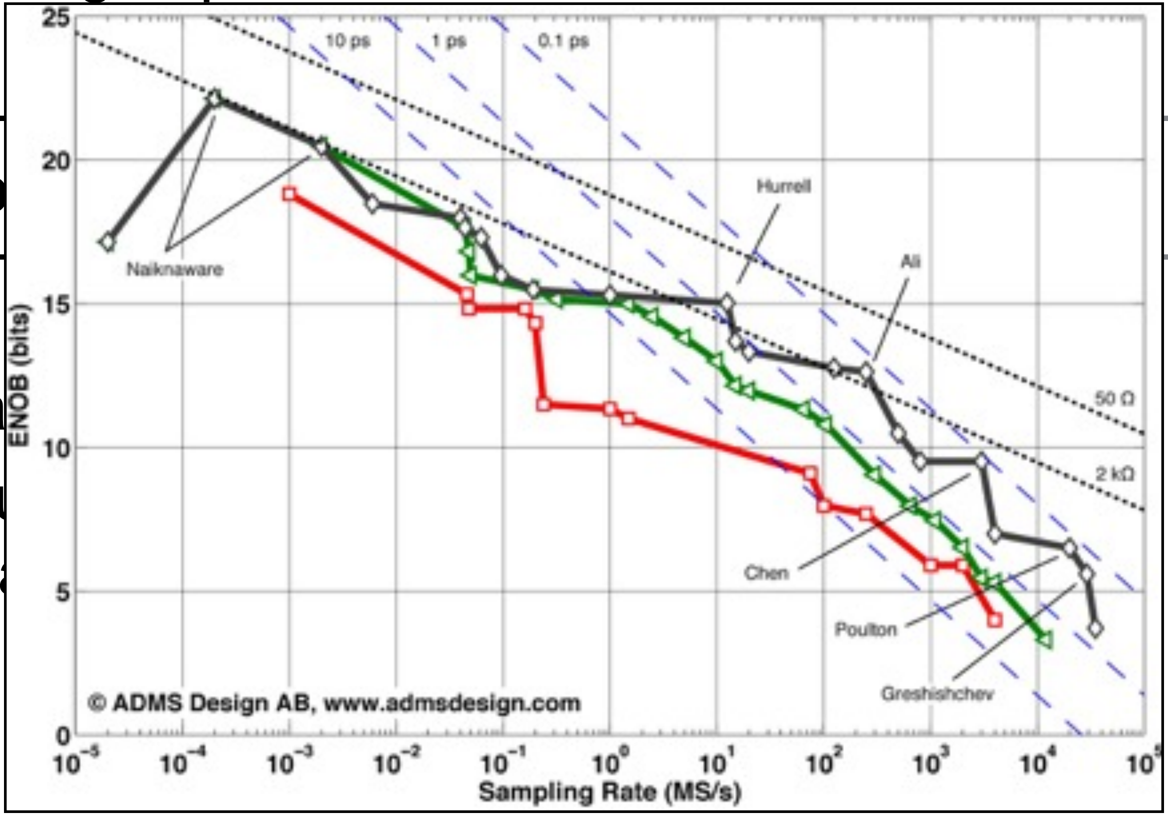
- Ultra-wide band Signal Processing
  – Huge burden on sampling devices is not manageable

CS-based A2I

- Why analog implementation?

Co

- Ultra
  - Hu
    m



CS-based A2I

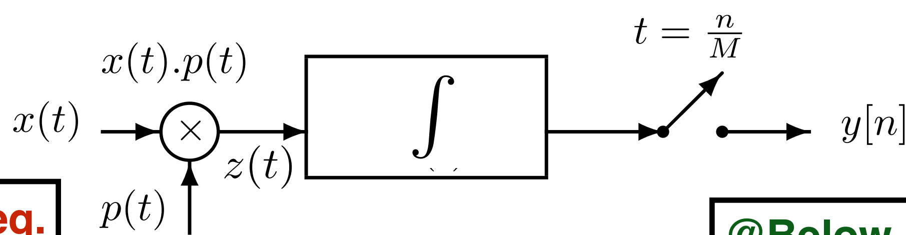
- Why analog implementation?

- Ultra-wide band Signal Processing
  - Huge burden on sampling devices is not manageable
- Power-aware sensing
  - By merging sampling and compression and thus removing large part of readout and digital processing part.

Random Modulator

- Signal Model: $x(t) = \sum_{i=1}^{n} \alpha_i \phi_i(t)$

- Random Modulator



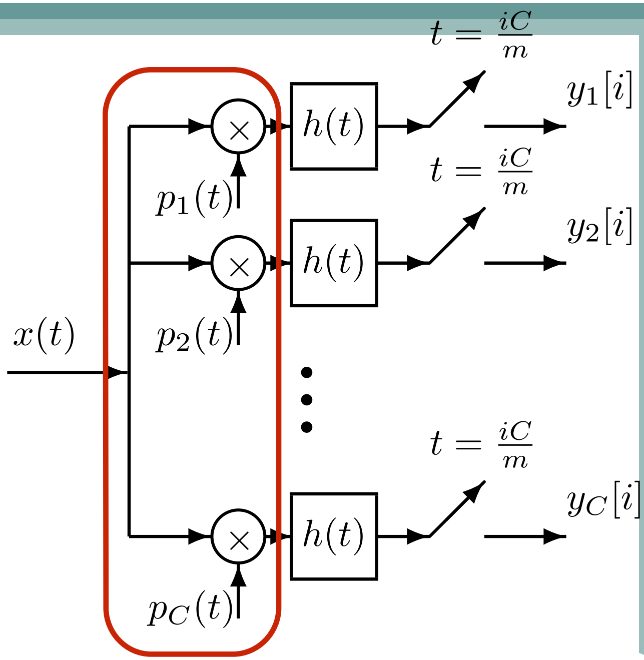
@Nyquist Freq.

@Below Nyquist Freq.

$$P_c(t) = p_i, \qquad t \in \left[\frac{i}{n}, \frac{(i+1)}{n}\right) \qquad i = 0, 1, \ldots, n-1$$

Analog CS: RMPI

- RMPI: Random Modulator Pre-Integrator
  - parallel RM channels
  - Further reducing ADC rate
  - Less measurement



- Limitations:
  - Exact representation of the digital CS means that number of channels should be equal to the number of measurements.
  - Random modulation (mixers) should work at Nyquist Frequency
  - higher number of channels is not practical!

Analog CS: RMPI

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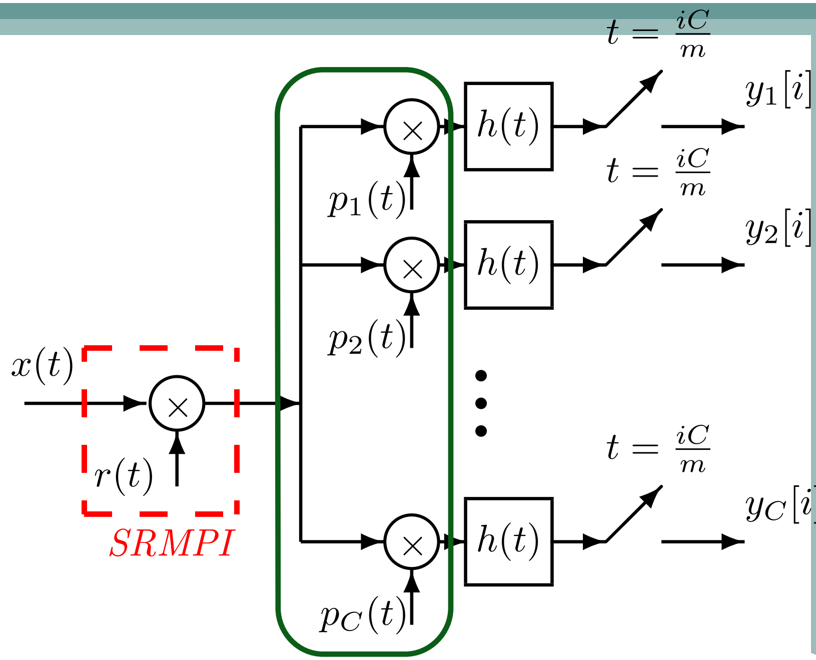
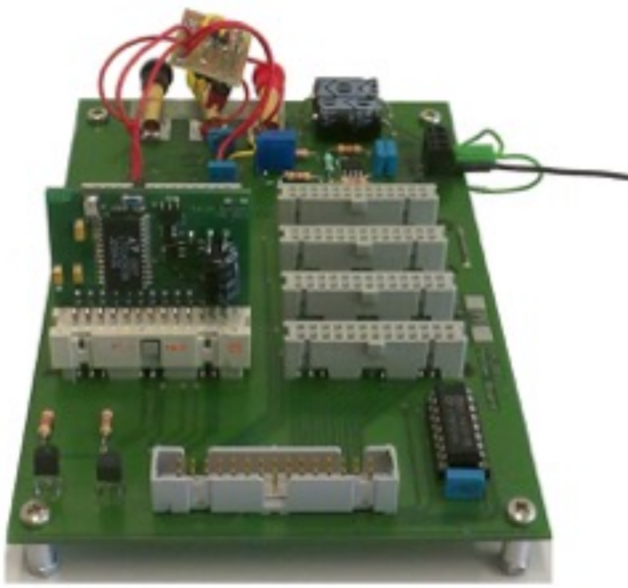


- New Architecture proposed to reduce number of channels in RMPI architecture and reduce random modulation called SRMPI.

  - The design is for highly sparse signals

Hardware Optimization: Analog CS

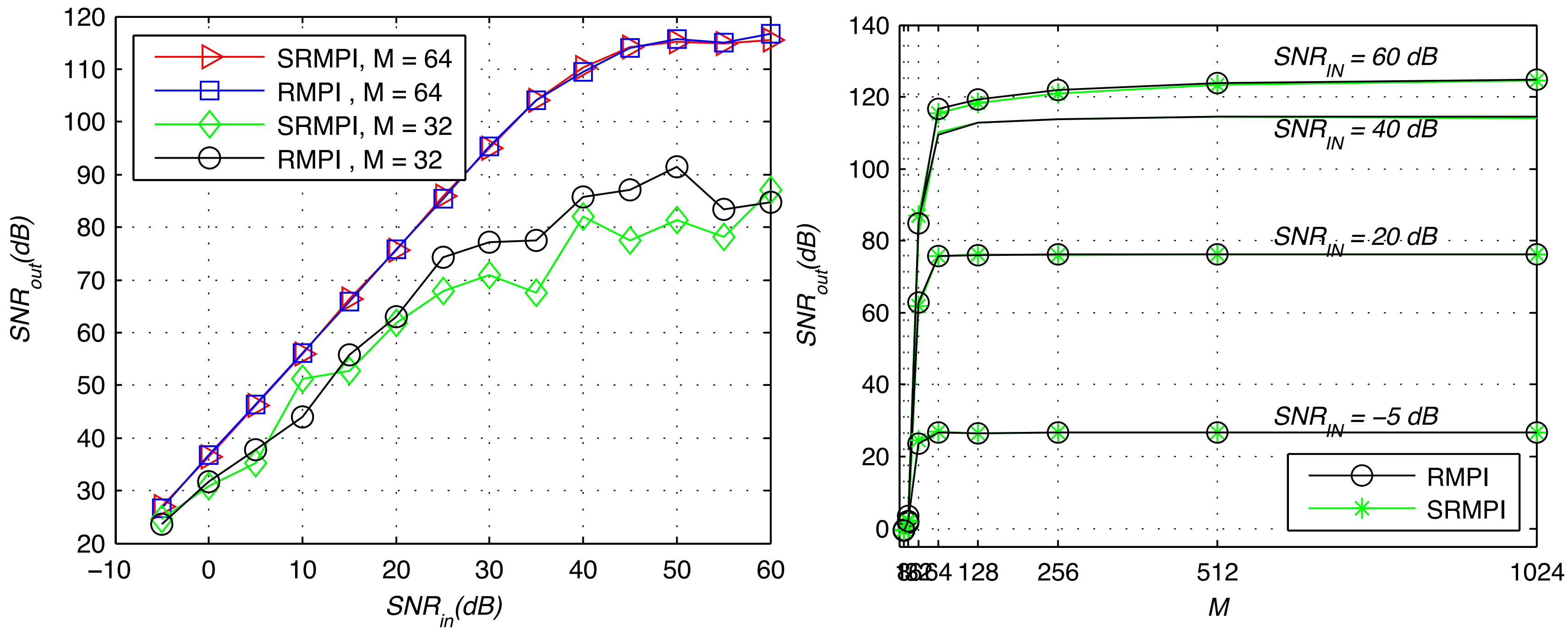
- 8-channel RMPI/SRMPI reconfigu
  implemented
  - Main board + 8 RM daughter b
- Connected to PC with DAC for rec
  communication
- SRMPI pre-modulation are implem
  (bypassed for RMPI)
  - modulation (CMOS Switch)
  - Integrator (Analog filter)
  - ADC



8-channel Implementation of Analog CS

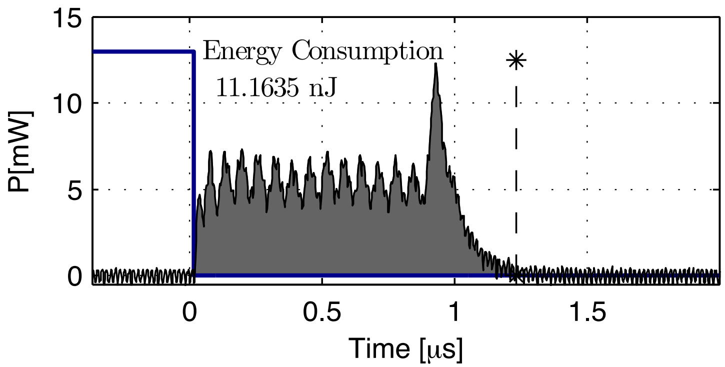
Experimental Results

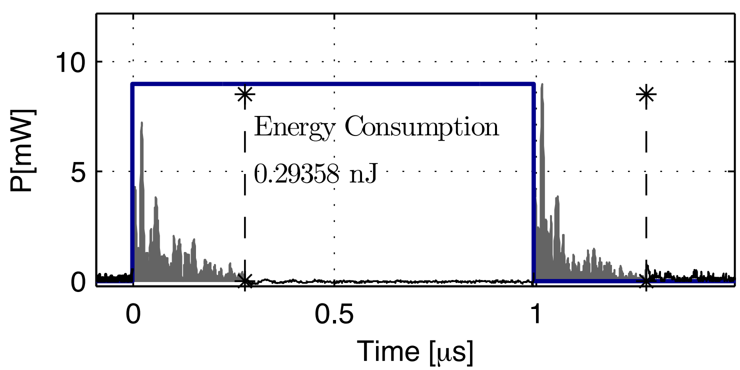
- Signal model: 3 tone (sinusoid)



Power break-down

- Power consumption of main blocks
  - ADC
  - Mixer (modulator)





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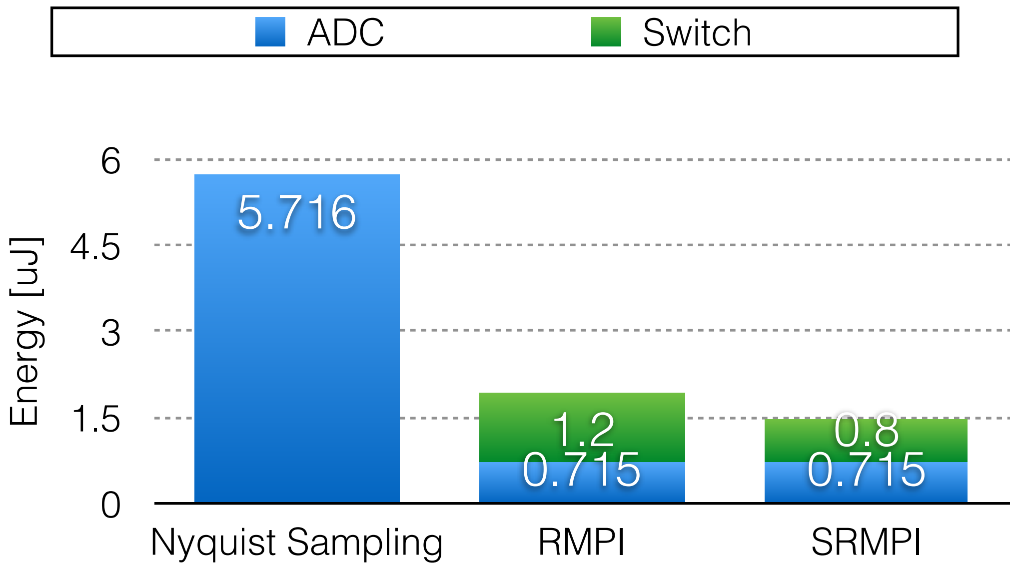

- **63%** and **75%** Reduction in power consumption by RMPI and SRMPI respectively.
- SRMPI outperforms RMPI by at least **25%**.

Outline

Software

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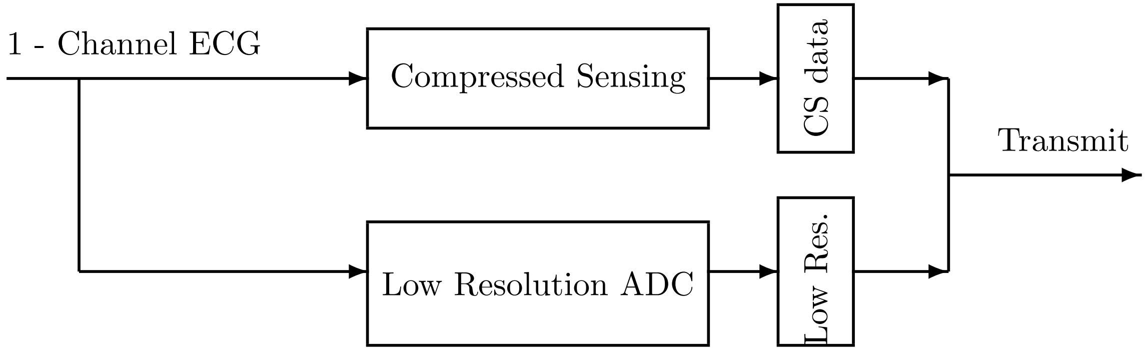
  - Robust Compressed Sensing

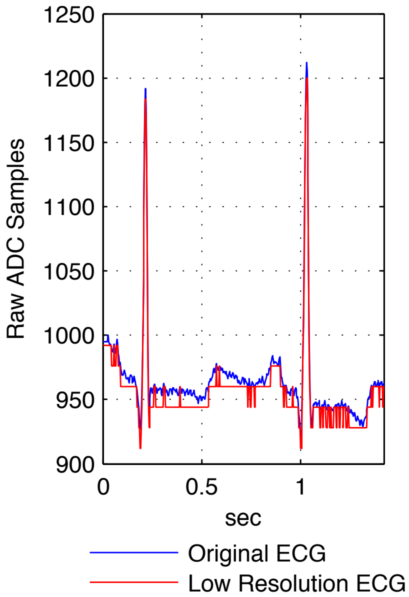
Hardware

- CS-based Analog to Information
  - **ECG ultra-low-power front-end design**

Hybrid CS-based Front-end

- New hybrid digital+analog design is proposed
  - Parallel low resolution channel
  - High resolution RMPI channel





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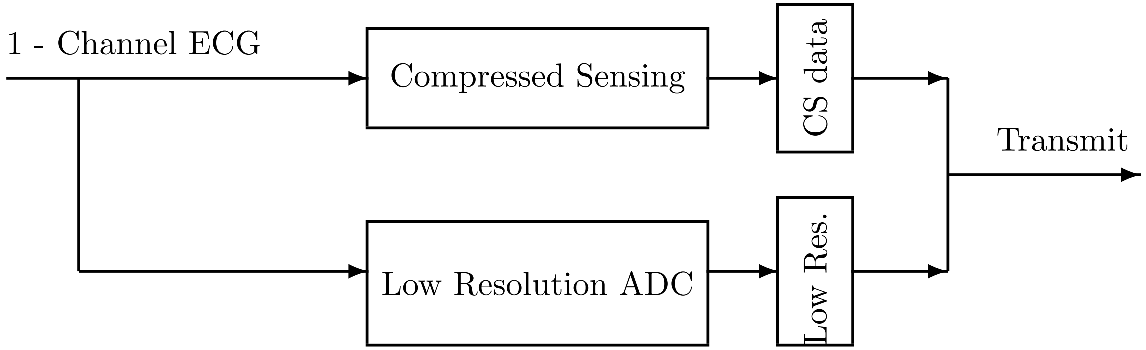

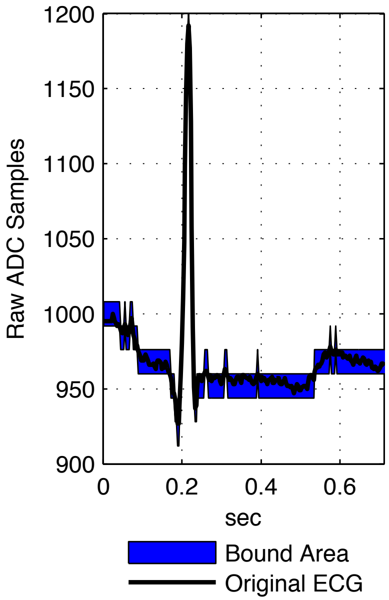

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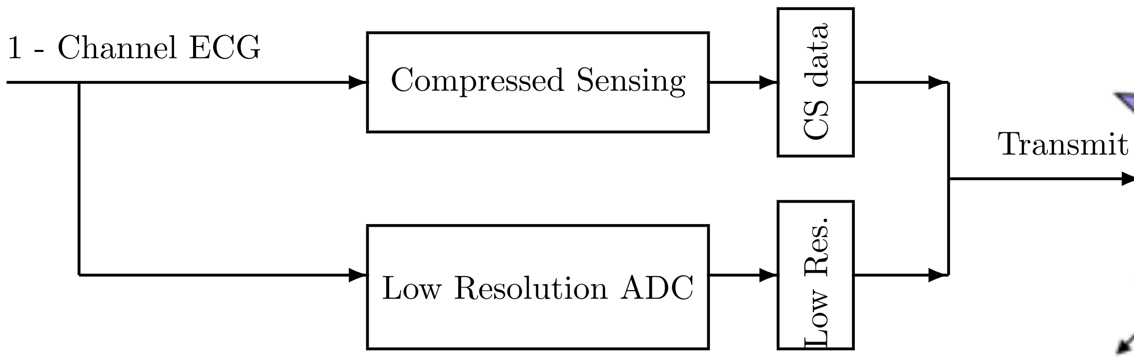
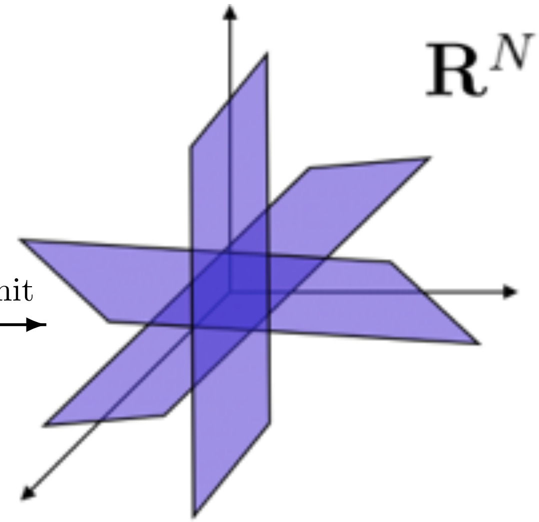
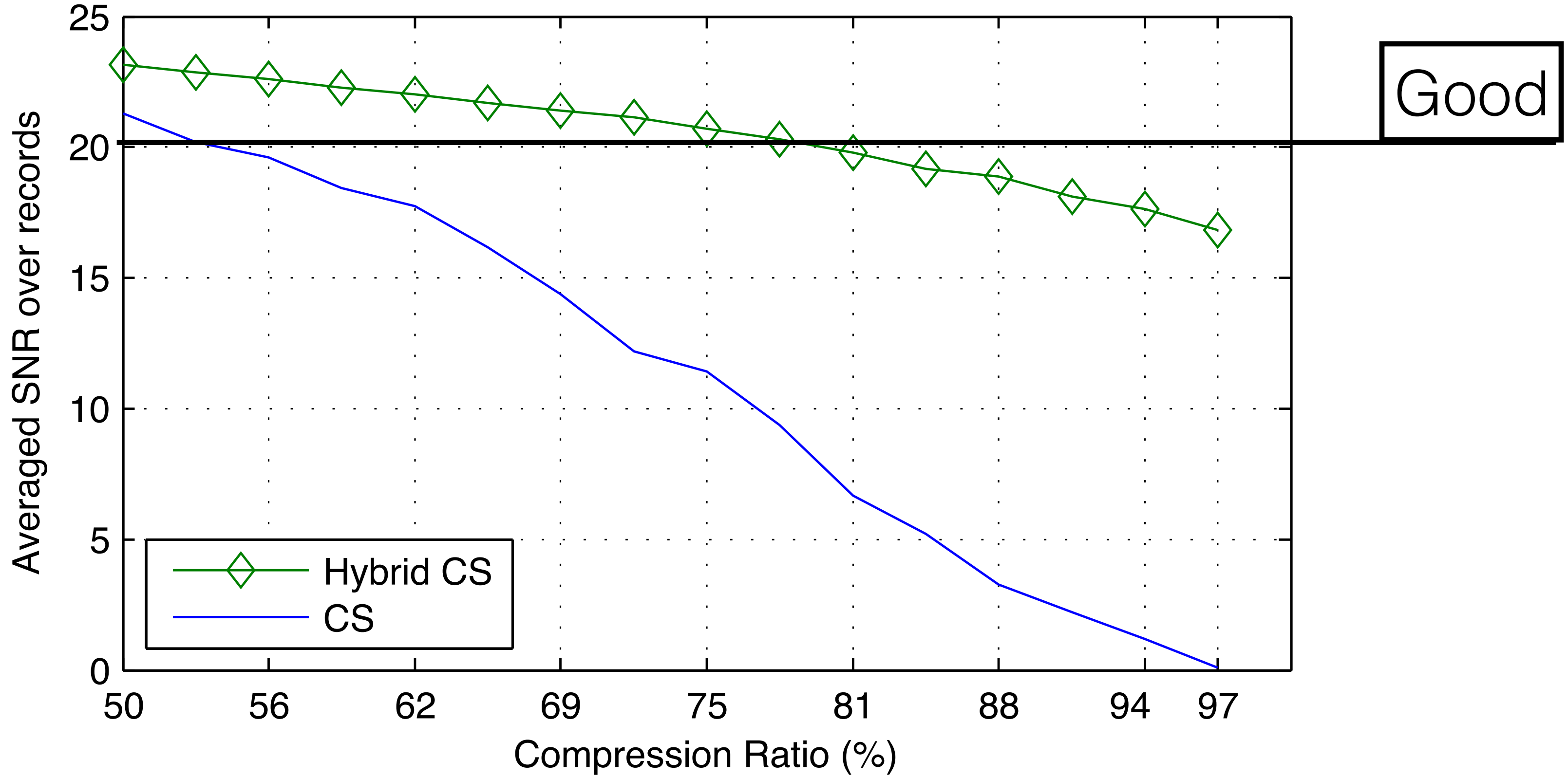




$$\min_{\tilde{\boldsymbol{\alpha}} \in \mathbb{R}^N} ||\tilde{\boldsymbol{\alpha}}||_1 \quad \text{subject to} \quad \begin{cases} ||\boldsymbol{\Phi}\boldsymbol{\Psi}\tilde{\boldsymbol{\alpha}} - \mathbf{y}||_2 \leq \sigma, \\ \boxed{\dot{\mathbf{x}} \leq \boldsymbol{\Psi}\tilde{\boldsymbol{\alpha}} \leq \dot{\mathbf{x}} + d} \end{cases}$$

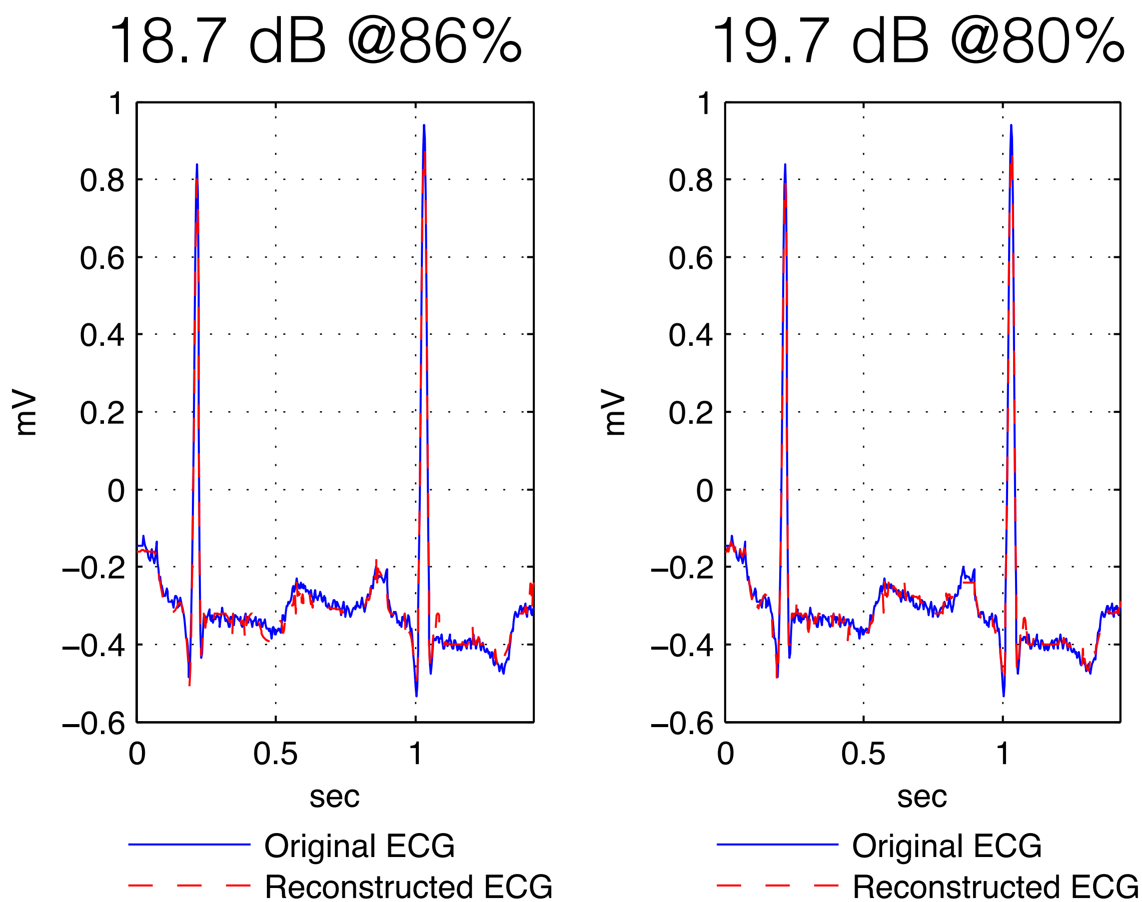
- **Relaxed RIP, fewer measurements**

Performance Quality Comparison



- **35 % reduction in compression ratio**
- Very good performance at higher CR (SNR = 17dB @97%)

Performance Quality Comparison



- **35 % reduction in compression ratio**
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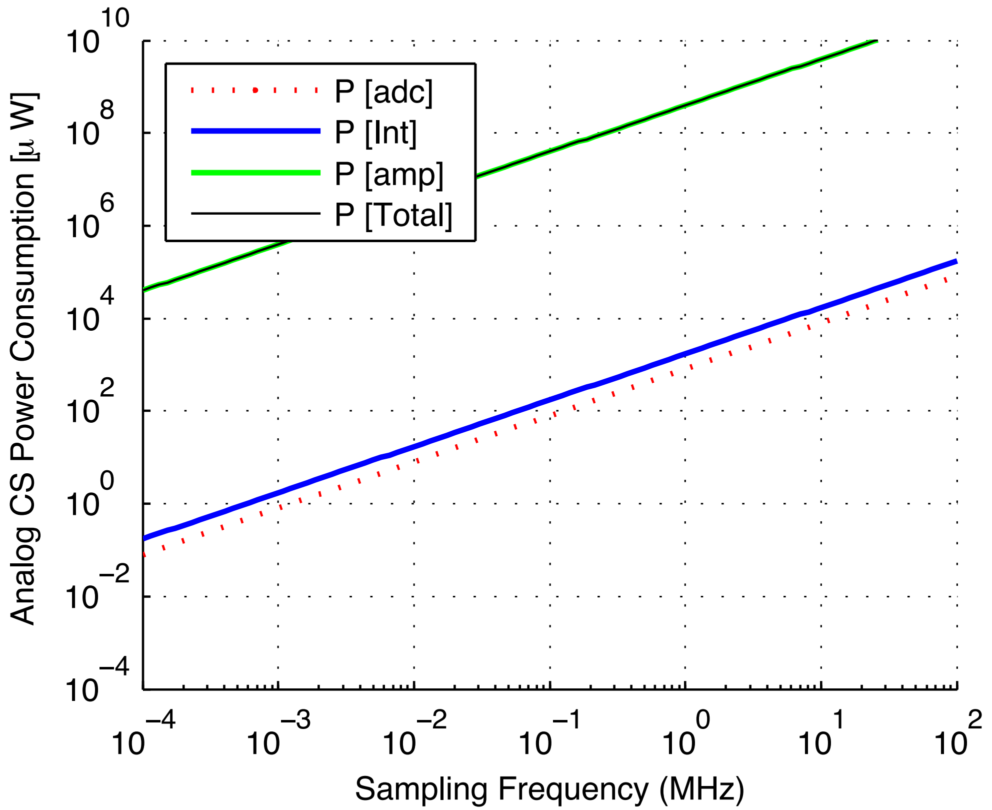
Power consumption break-down

- Power break down



2.5 X Power reduction compared to RMPI at Good quality
11 X reduction at SNR = 17dB (number of channels = 16)

Conclusion

- Smart ULP WBSN nodes needed to enable new healthcare
  - Feasible to do real-time automated biosignals analysis
  - Communication not always the worst part: sensing and processing
- Knowledge about target bio-signals not to over-design WBSNs
  - Compressed sensing very powerful approach (if used with care)
  - Removes need for complex instructions sets and limits memory use
- New ULP WBSN multi-parametric architectures coming up
  - Adaptive to each patient (big data link!)
  - Joint compressive sensing can help to significantly save power
- Novel field: wearable multimodal biosignal systems
  - **Develop uses of these new WBSNs to monitor other emotions, etc.**
  - **Design methods to ease low-power software mapping needed!**

Thank You

QUESTIONS?

Acknowledgments:

PHIDIAS and ICT energy

ObeSense, BodyPowerSense, BioCS Projects in Nano-Tera.ch

Thanks to our great collaborators:
LTS2-EPFL, TCL-EPFL and IIS-ETHZ

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