

# PROS: an Efficient Pattern-driven Compressive Sensing Framework for Low-Power Biopotential-based Wearables with On-chip Intelligence

**Nhat (Nick) Pham**<sup>1</sup>, Hong Jia<sup>2</sup>, Minh Tran<sup>1</sup>, Tuan Dinh<sup>3</sup>, Nam Bui<sup>4</sup>, Young Kwon<sup>2</sup>, Dong Ma<sup>5</sup>, VP Nguyen<sup>6</sup>, Cecilia Mascolo<sup>2</sup>, and Tam Vu<sup>4</sup>

<sup>1</sup>University of Oxford, <sup>2</sup>University of Cambridge, <sup>3</sup>University of Wisconsin Madison, <sup>4</sup>University of Colorado Boulder, <sup>5</sup>Singapore Management University, <sup>6</sup>University of Texas at Arlington.

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# Motivation

What can we enable w/ 40X high-fidelity biosignal compression on wearables?



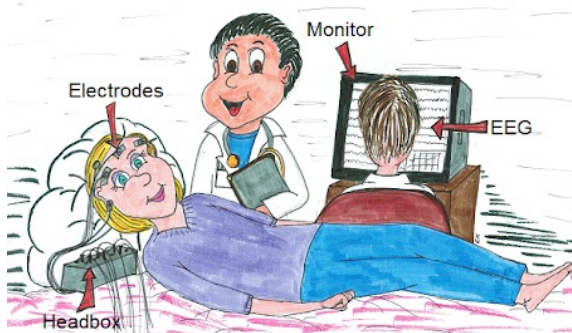
**Prevent fatalities!**



**Enhance usability!**

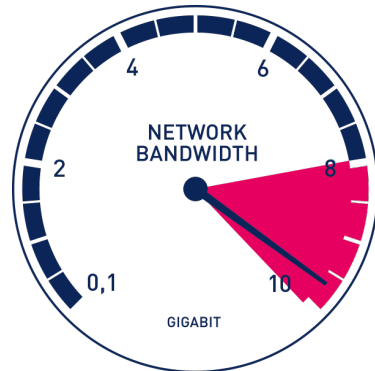
# The problem

**Many healthcare biosignal-based applications are not practical for wearables!**



**Long-term, high-fidelity monitoring**

**Weeks/Days not hours!**



**High data rate**

**Communication is energy heavy!**



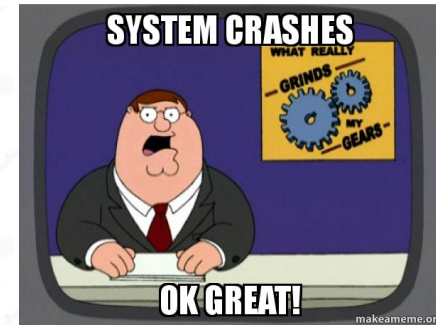
**Low-latency response**

**Slow responses could be fatal!**



**Small battery, resource-constrained devices**

**MHz CPU, KB Memory!**



# The conventional trade-off

## Signal Quality



### Medical Biosignal Monitoring

Brain/Eyes/Muscle: 10-20x1024Hz.  
Battery life: >24h, w/ a big bag of batteries  
Need constant monitoring by technicians.

VS.

## Battery Life

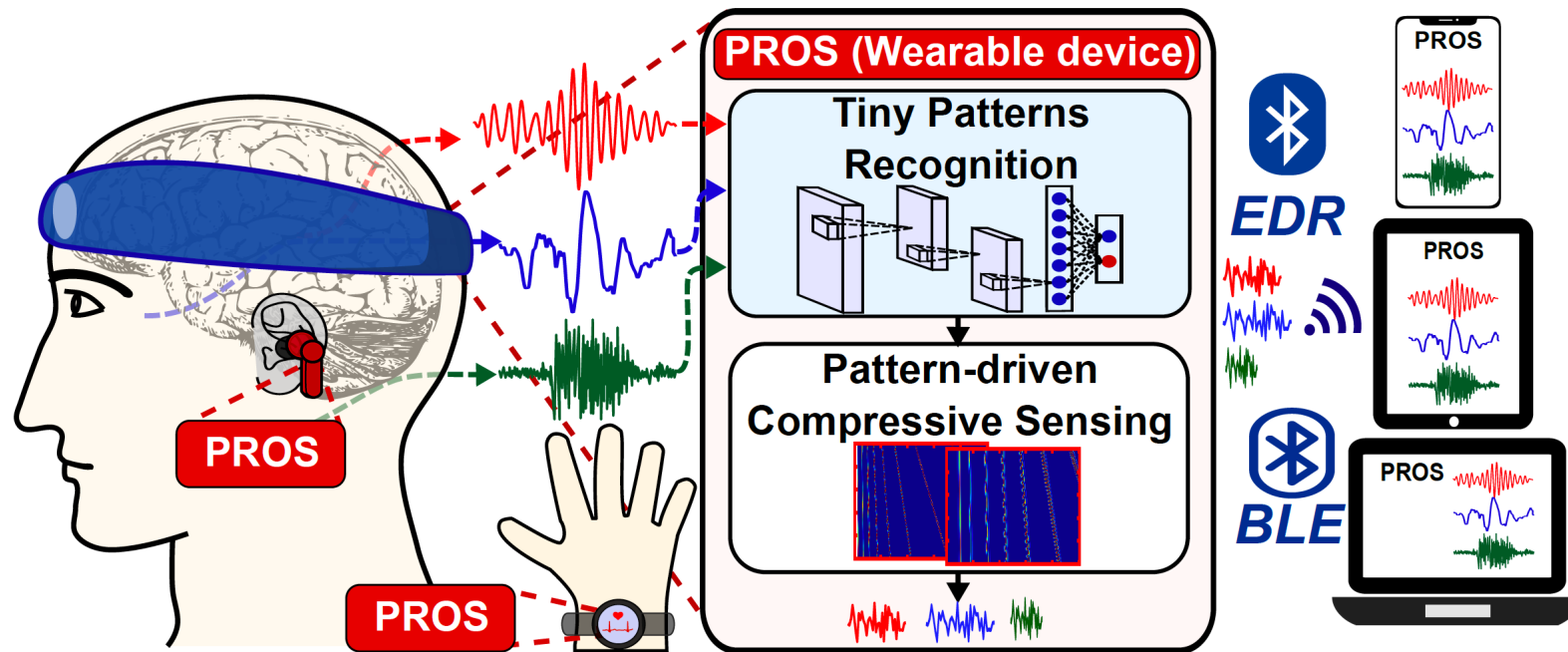


### Embrace2 Wearable

Battery life: 48h  
Sweat: 4Hz (vs 512Hz in diagnostic)  
Motion: 3x32Hz, Temp.: 1Hz.  
Real-time alerts through a mobile app.

**A new solution is needed to overcome this trade-off!**

# Our proposed Pattern-dRiven cOmpressive Sensing (PROS) system



Long battery life

High fidelity biosignals

Low-latency responses

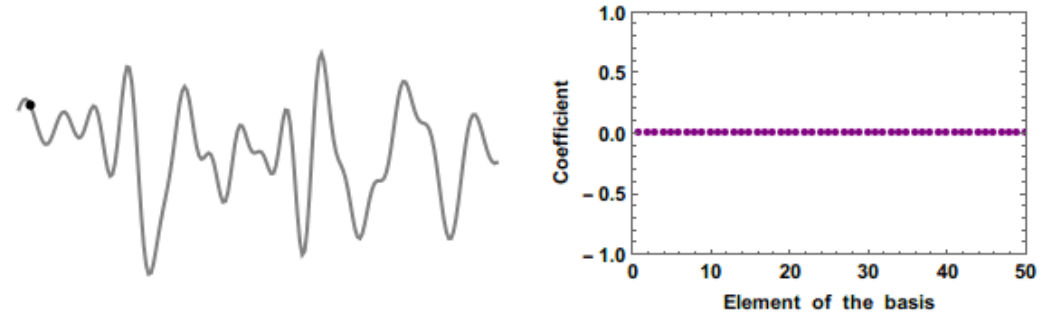
Computational efficiency

# Observations

❑ #1: Biosignal events are sparse!



❑ #2: Biosignals are (potentially) sparse!

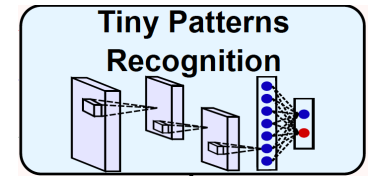


**Exploiting event and signal sparsity -> significant streaming data reduction**

❑ #3: However, developed algorithms need to be efficient!



# Challenge #1: How to detect biosignal events efficiently on wearables? (1/2)

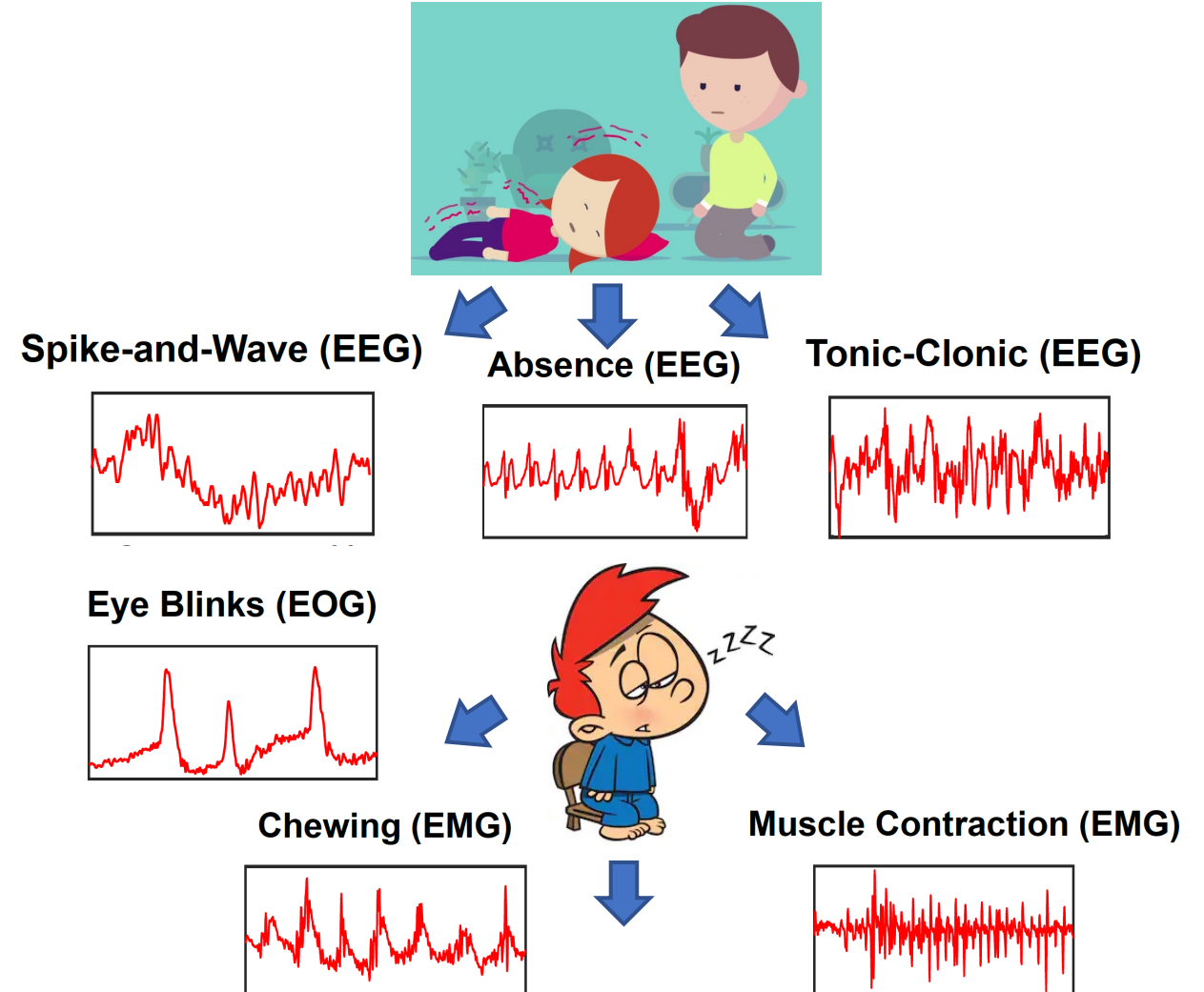


## ❑ Detection of **biosignal events on wearables** is challenging!

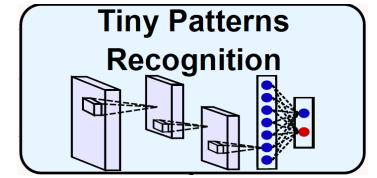
- **Multiple signal modalities** (e.g., EEG, EOG, EMG, etc.)
- **Constrained hardware and energy resources.**



**Complex biosignal events can be broken down into patterns of interest (Pols)!**



# Challenge #1: How to detect biosignal Pols efficiently on wearables? (2/2)



## □ Tiny Pattern Recognition models (TinyPRs)

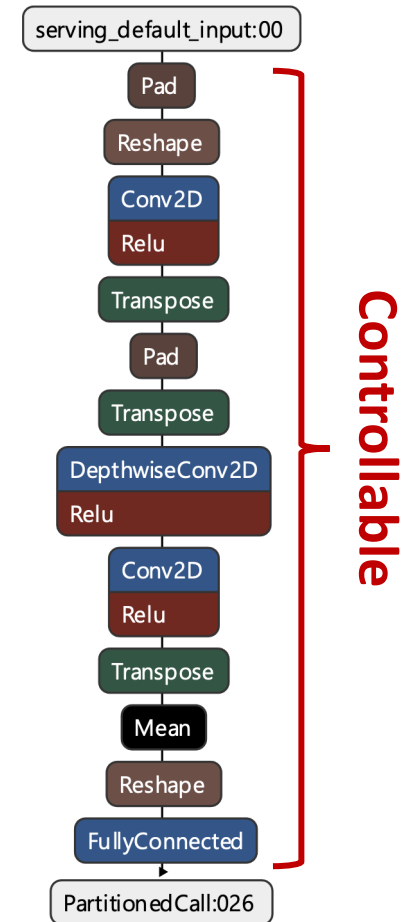
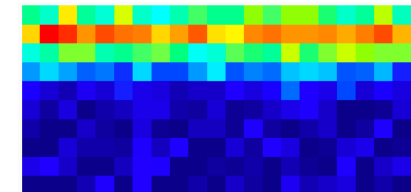
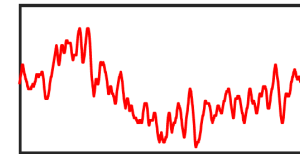
- Each TinyPR detects one pattern.
- Fine-tuned feature extraction (MFCC).
- Flexible Depth-wise and Point-wise Convolution layers.
- Accelerated by SIMD and DSP.



How can we push the data transmission reduction further?



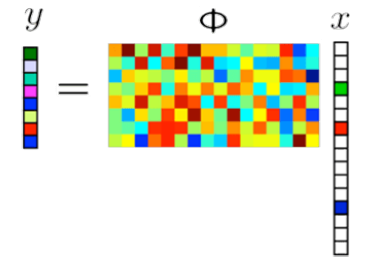
Spike-and-Wave (EEG)



Pattern probability



# Challenge #2: How to compress the detected Pols? (1/2)



❑ Biosignals are potentially sparse in time-frequency domains (wavelets, Gabor, etc.), but...

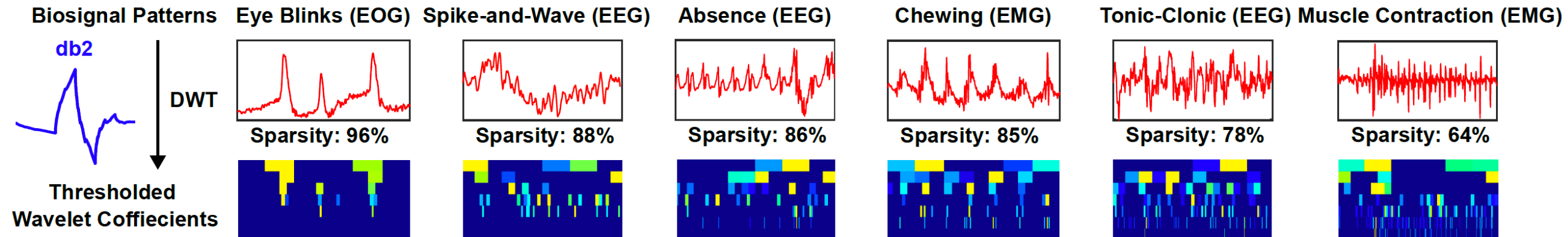
- **Large variations** among channels and trails. -> **sub-optimal compression!**
- **A universal optimal sparse domain might not exist.**



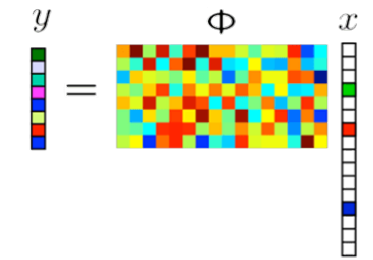
**Optimal domains for individual biosignal patterns!**



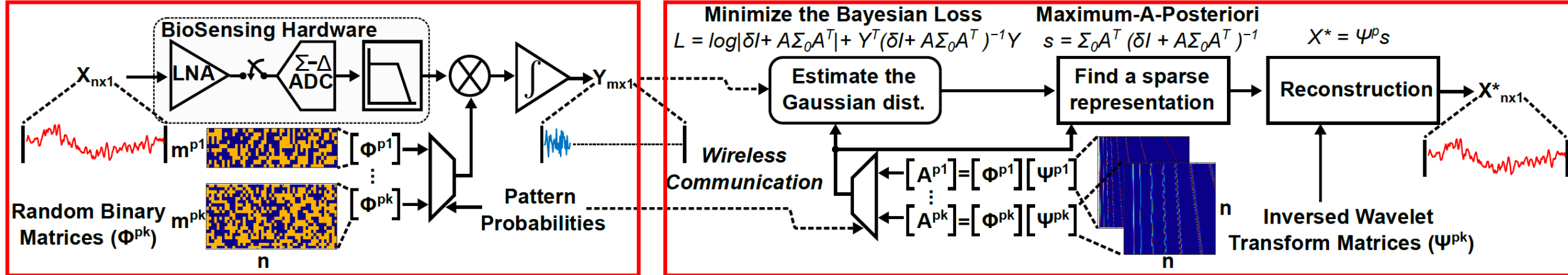
**Optimal Wavelet Search Algorithm**



# Challenge #2: How to compress the detected Pols? (2/2)



## □ Pattern-driven Compressive Sensing (CS)



### ○ Wearable device:

- **Pattern probability** from TinyPRs.
- **Dynamic Random Binary Matrices** compressing based on the detected patterns.

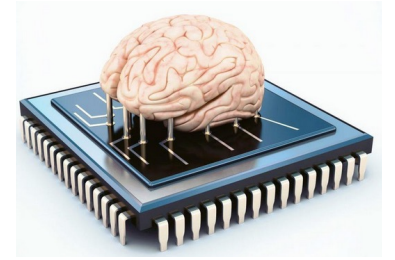
### ○ Mobile device:

- Biosignal reconstruction based on **Block Sparse Bayesian Learning**.
- **Dynamic wavelet domains selection** on the fly.



**Processing efficiency?**

# Challenge #3: How to optimise processing efficiency? (1/1)



## ❑ Dynamic Frequency and Voltage Scaling (DVFS)

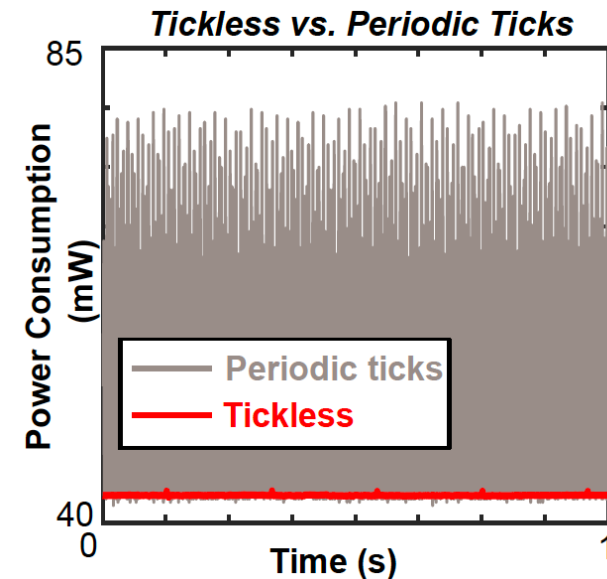
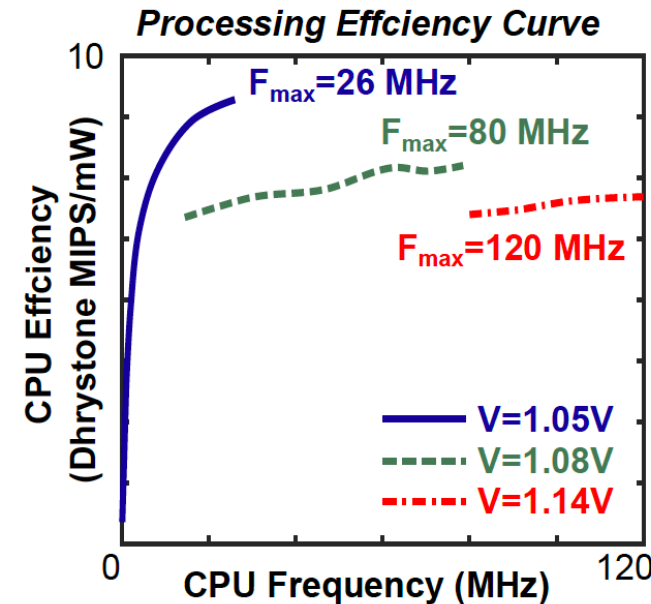
- Choose the optimal CPU efficiency point based on application's requirements.
- ↑ CPU Frequency -> ↑ Sleep time -> ↑ Voltage

## ❑ Adaptive Energy Detector

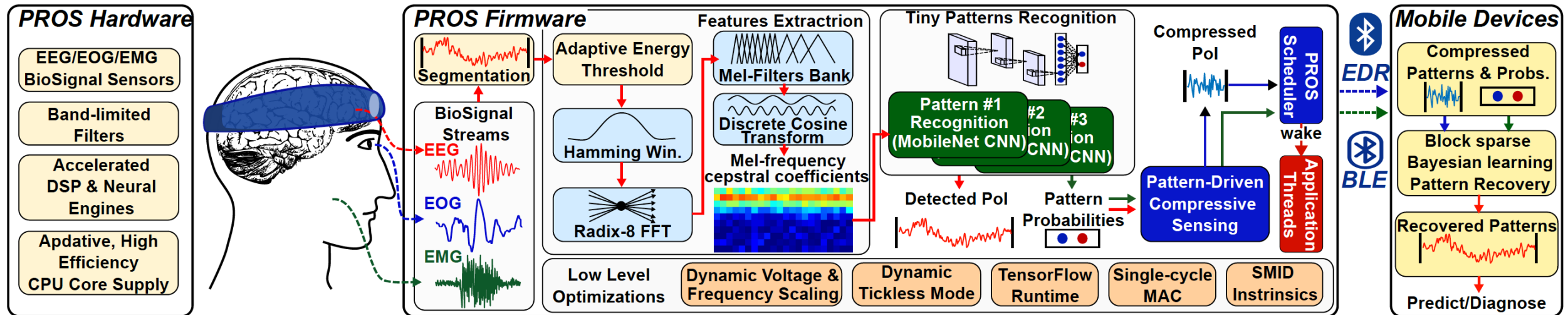
- Some background signals are too obvious for TinyPRs!

## ❑ Tickless Kernel Mode

- Eliminate periodic CPU wake-ups!
- Ultra-low power interrupt-based timebase.



# Implementation



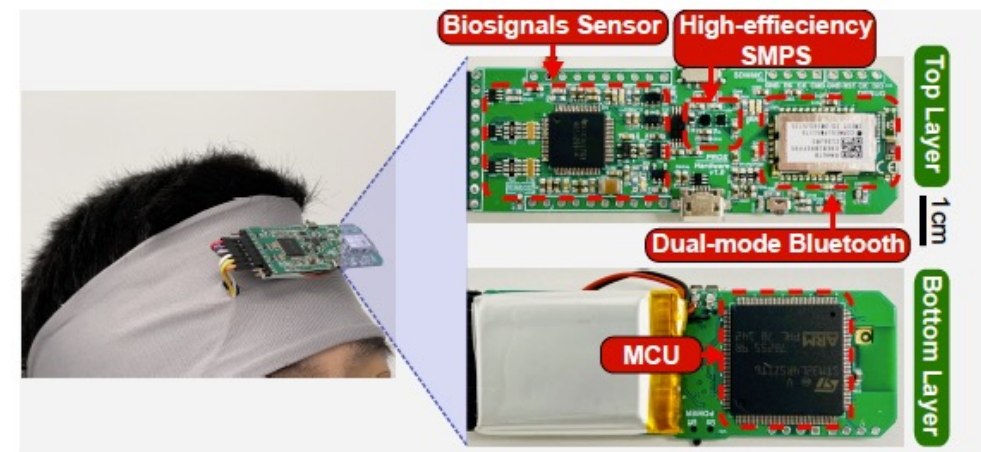
## Wearable

- Low-power ARM MCU, 120 MHz, 1MB FLASH, 256KB RAM,
- TinyPR pipeline,
- Pattern-driven Compressive Sensing,
- Hardware and low-level optimisations.

## Mobile

- Surface Go, Galaxy S20,
- Reconstruction algorithm.

## System Overview

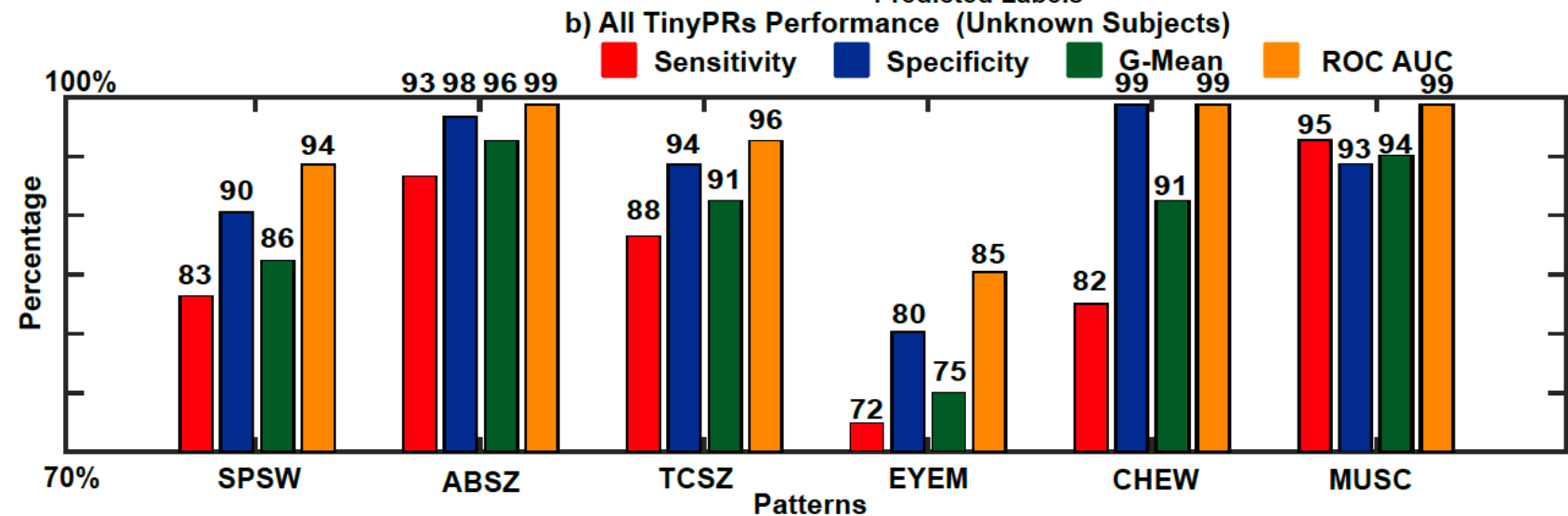
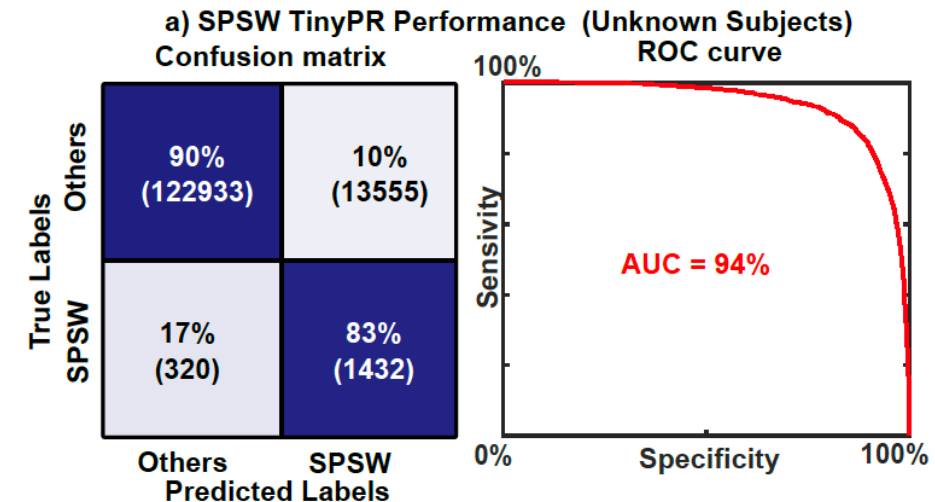


Optimised biosensing hardware

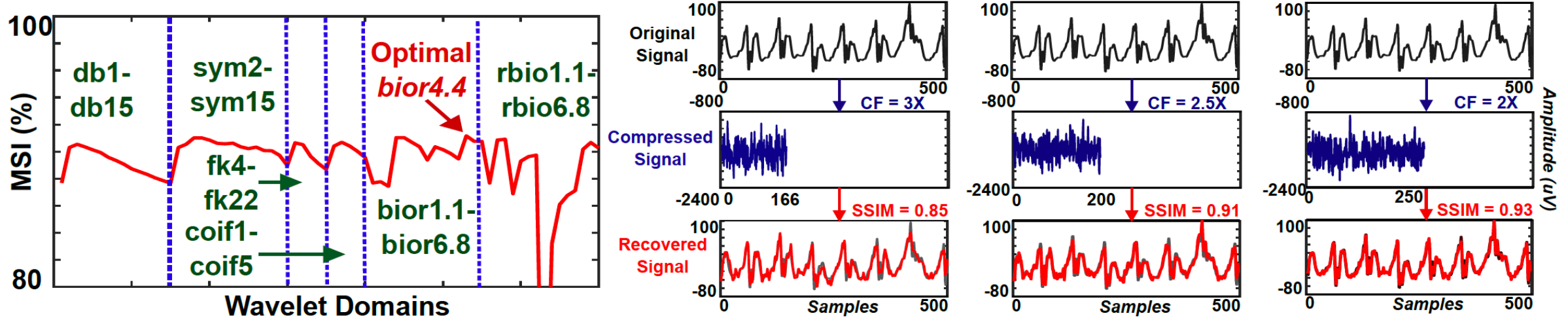
# Evaluation #1 – Tiny Pattern Recognition Performance

## □ TinyPR's performance:

- 2 open datasets (hospital settings).
- 6 biosignal patterns.
- 120 subjects (100 train/20 test), 2,099,479 data points.
- **75% - 96% Sensitivity and Specificity** on unseen subjects.



# Evaluation #2 – Pattern-Driven Compressive Sensing Performance



## Optimal wavelet search

- 71% - 93% sparsity for each biosignal pattern.

## CS performance:

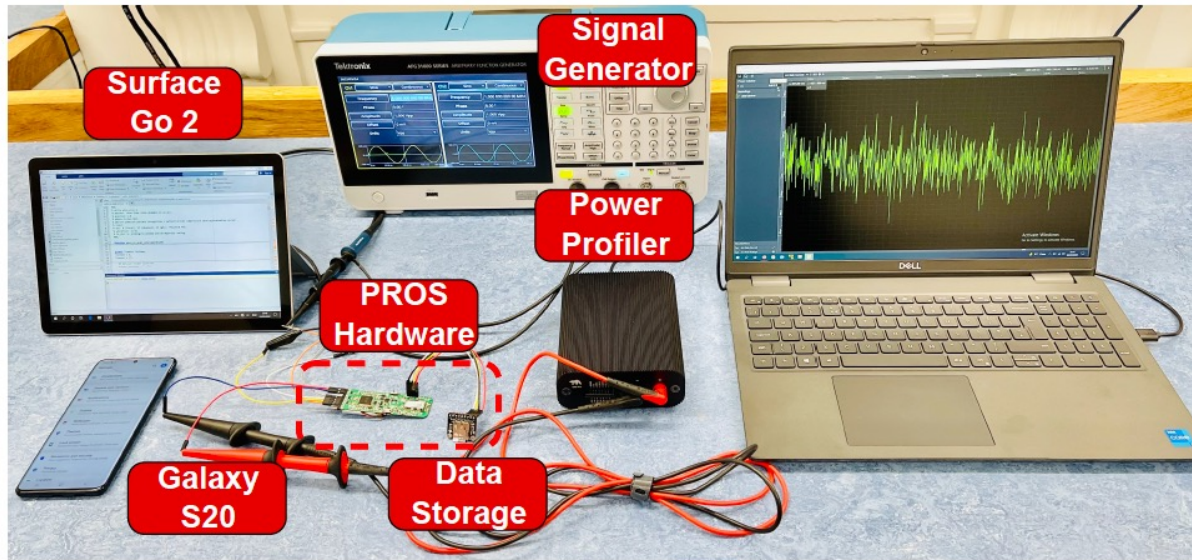
- Up to 5X compression (CS alone)
- Up to 40X compression (CS + TinyPR)

Table 1: Recovery quality with different CFs.

Pattern	Wavelet Domain	MSI (%)	SSIM with different CFs (w=3s)				
			1.5X	2X	3X	4X	5X
SPSW	bior6.8	92.6	0.99	0.98	0.96	0.94	0.89
ABSZ	bior4.4	91.2	0.99	0.97	0.94	0.89	0.82
TCSZ	sym14	71.4	0.84	0.81	0.57	0.39	0.31
EYEM	sym5	89.6	0.98	0.97	0.91	0.84	0.80
CHEW	bior4.4	84.0	0.93	0.93	0.84	0.78	0.71
MUSC	sym5	79.7	0.92	0.88	0.70	0.60	0.50

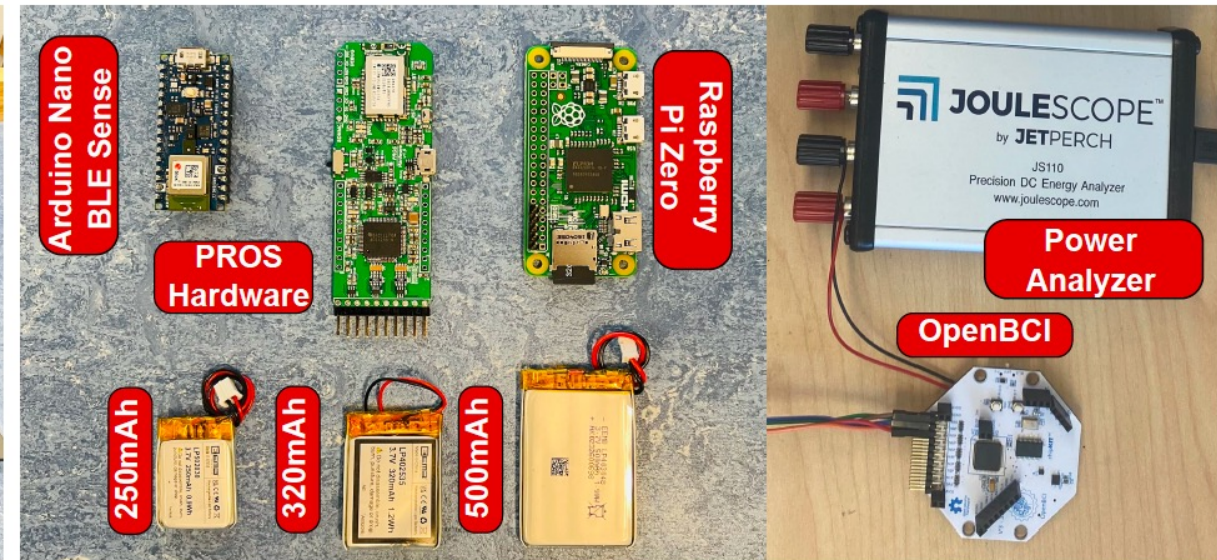


# Evaluation #3 – Hardware runtime performance



## ❑ Hardware performance

- **TinyPR:** 5KB FLASH, 30 KB RAM, 26ms (@120MHz).
- **CS:** 4-30KB FLASH, 1ms (Wearable), 50-94ms (Mobile devices)



## ❑ Epileptic Seizure Monitoring use case:

- **10 unseen subjects:** 277,662 data points.
- **3 patterns:** Focal, Absence, Tonic-Clonic.
- **High-fidelity:** 85% Sensitivity, 0.92 SSIM.
- **Transmission reduction:** 24X.
- **Energy improvement:** >1200%.
- 500mAh -> last the whole week.
- Able to **detect fatal tonic-clonic seizures** < 32ms.

# Future work

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## ❑ Future work:

- **Improve pattern recognition performance.**
- **Extending and sharing ability for various signals and multiple applications.**
- **In-the-wild evaluations.**

## ❑ Open-source resource:

- <https://github.com/PROS-public>. (LGPLv2 License)

*Thank you for your attention!*

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