Low-Power Communication through Analog-to-Feature Conversion

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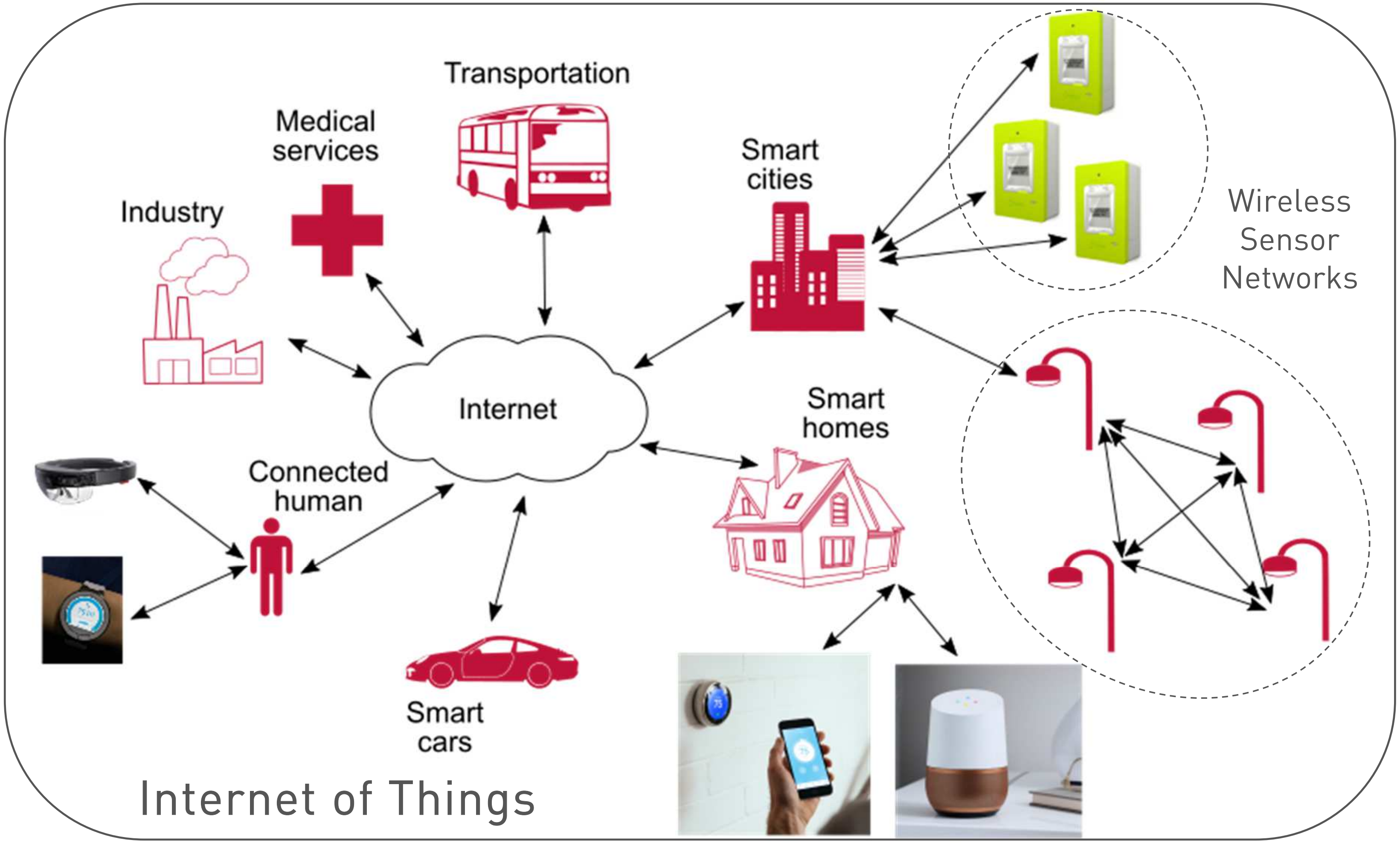
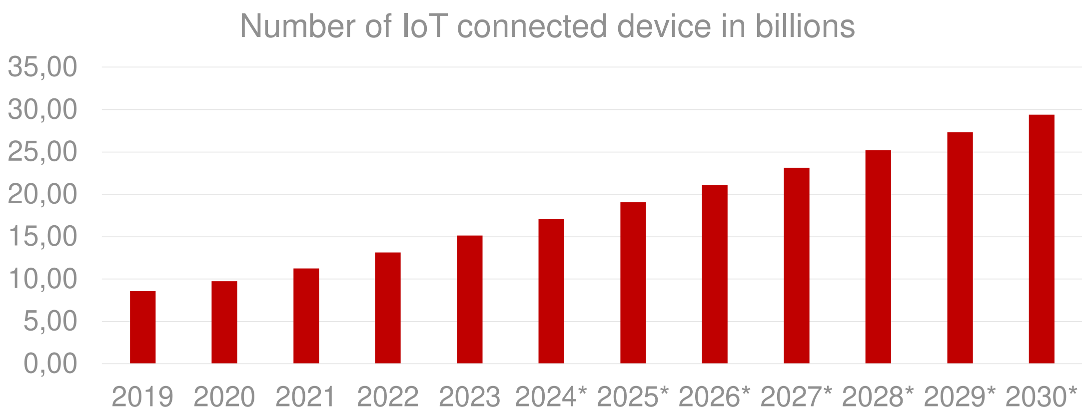
Internet of Things



Internet of Things : a few numbers



Source: Statista 2023

By 2025 :

- 152 200 IoT devices connecting to the internet per minute
- 4 to 11 trillions USD in economic value generated
- 73,1 Zettabyte (10^{21} Bytes = 1 billion TB) of data generated

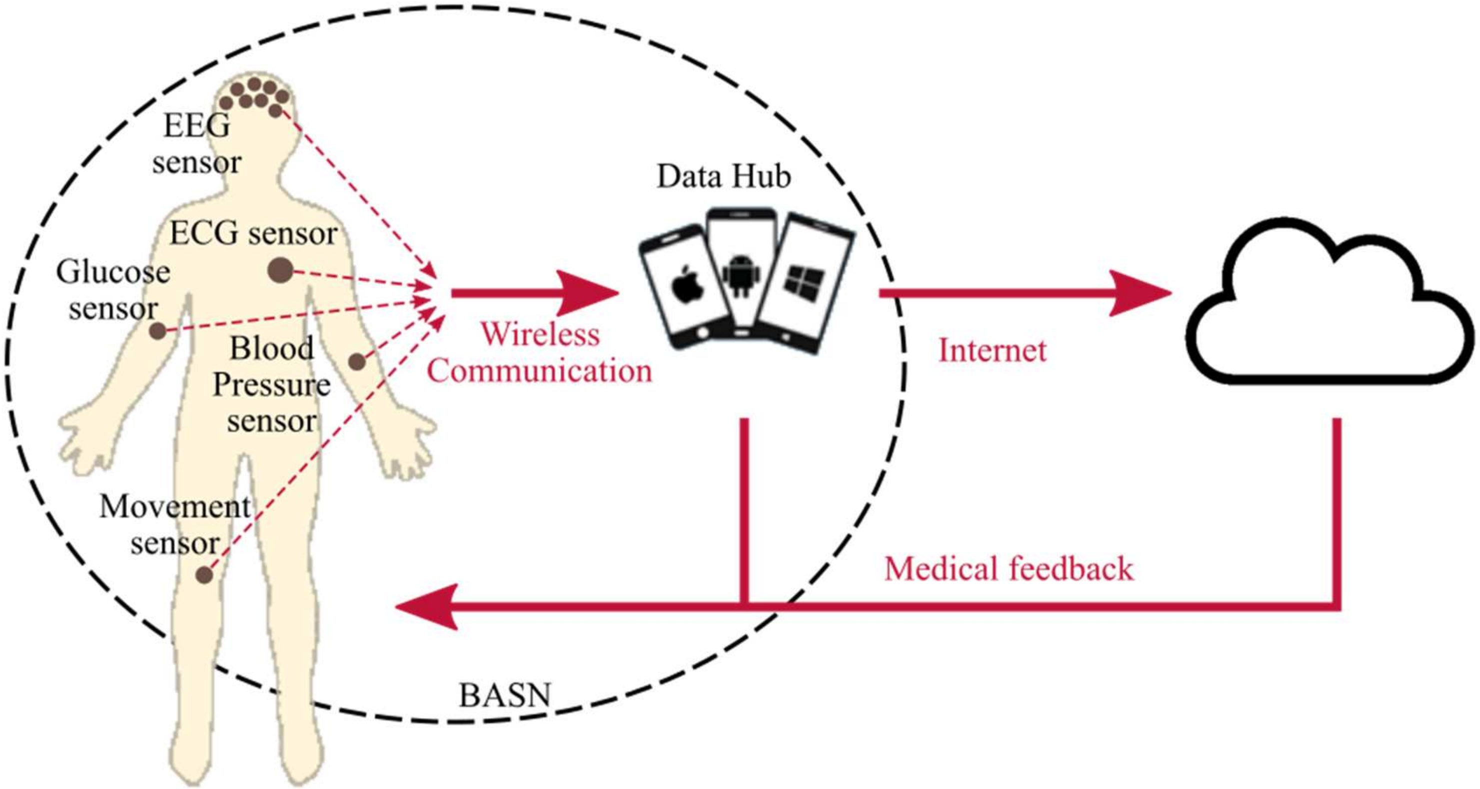
Source: https://dataprot.net/statistics/iot-statistics/

Presentation summary

1. Wireless Sensor Networks
2. Analog-to-Feature Conversion
3. Application to ECG
4. Conclusion and Future Work

Wireless sensor network architecture

Example of the Body Area Sensor Network



New challenges

Security

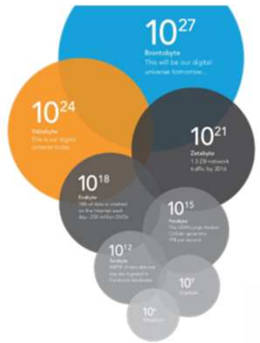
- Data confidentiality and integrity
- Security mechanisms embedded into circuits

Interoperability

- Interferences between WSN
- Specific communication protocols

Data transfer

- Increasing amount of data and bandwidth
- Saturation of the RF spectrum



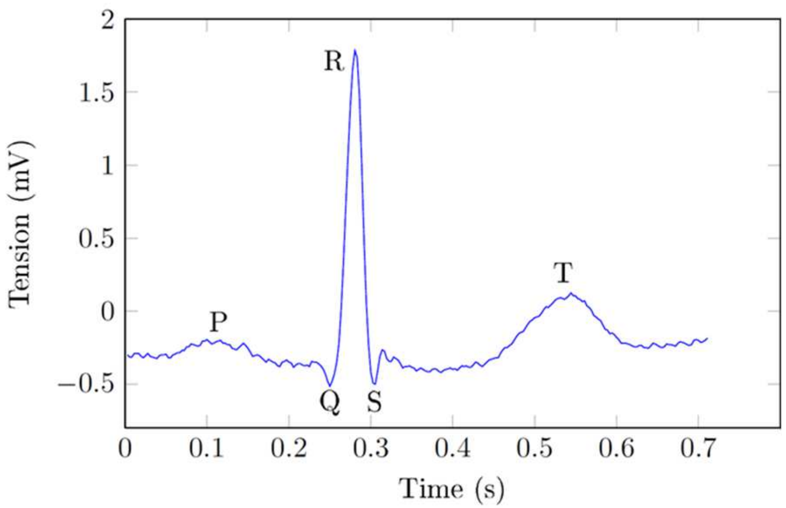
Power consumption

- Sensor working on batteries
- Energy source replacement is not always possible

Case study: electrocardiogram (ECG) signal

Cardiac arrhythmia detection

- Heart diseases responsible for 15.5 % of worldwide death
- Well studied subject



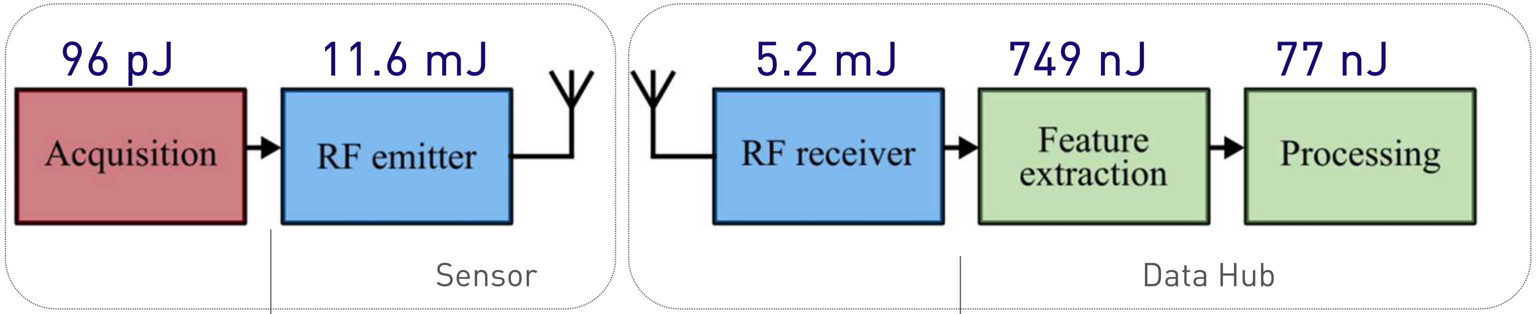
ECG signal characteristics

- Continuous signal
- Cycle duration: 0.5 – 0.9 s
- Sampling frequency: 200 – 1000 Hz
- Precision: ~ 10 bits

Application

- Arrhythmia detection from [1]
- Signal is 800 10-bit samples
- 1 kHz sampling frequency

Case study: simple sensor



Analog-to-digital converter [2]

- 0.18 µm CMOS
- 0.12 pJ/sample

Bluetooth Low Energy transceiver [3]

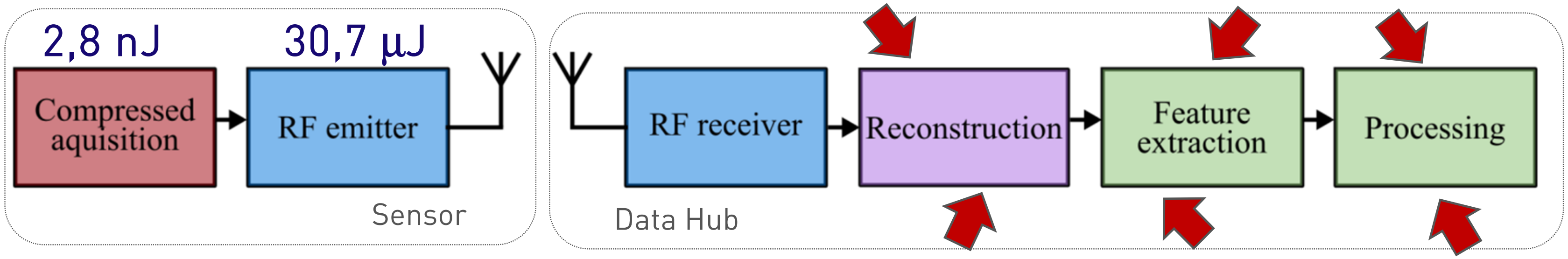
- 0.13 µm CMOS
- Emitter: 14.5 mW
- Receiver: 6.5 mW

Arrhythmia detection with linear classification [1]

- 0.13 µm CMOS
- Post-layout simulation

Transmission require the most energy

Case study: using compression



Compress the data during acquisition: compressed sensing

- Use knowledge on signal structure (sparsity)
- Reduce the amount of data to be transmitted

Analog-to-information (A2I) converter [4]

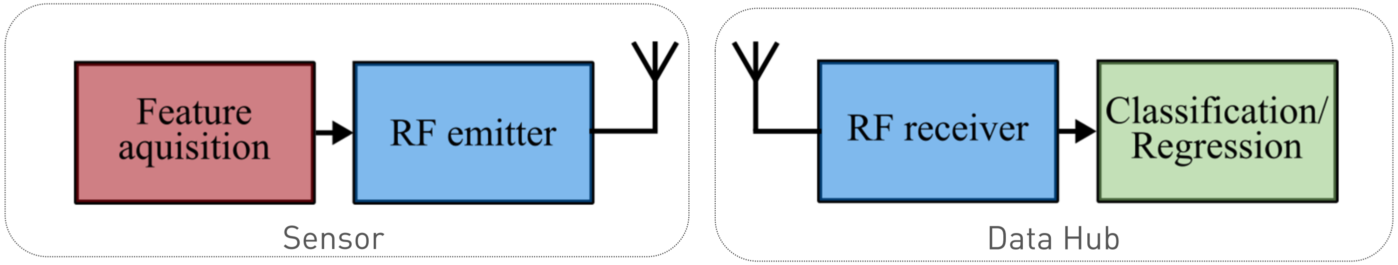
- 0.13 µm CMOS
- Compression ratio of 4
- 14 pJ/compressed sample

Sensor energy requirement is divided by 377

Limitations

- Reconstruction Algorithm is complex
- Reconstruction error increases with the compression factor

Proposed solution



Extracts only useful features

- Relevant to some specific task
- Directly from the analog signal

→ Analog-to-Feature Conversion

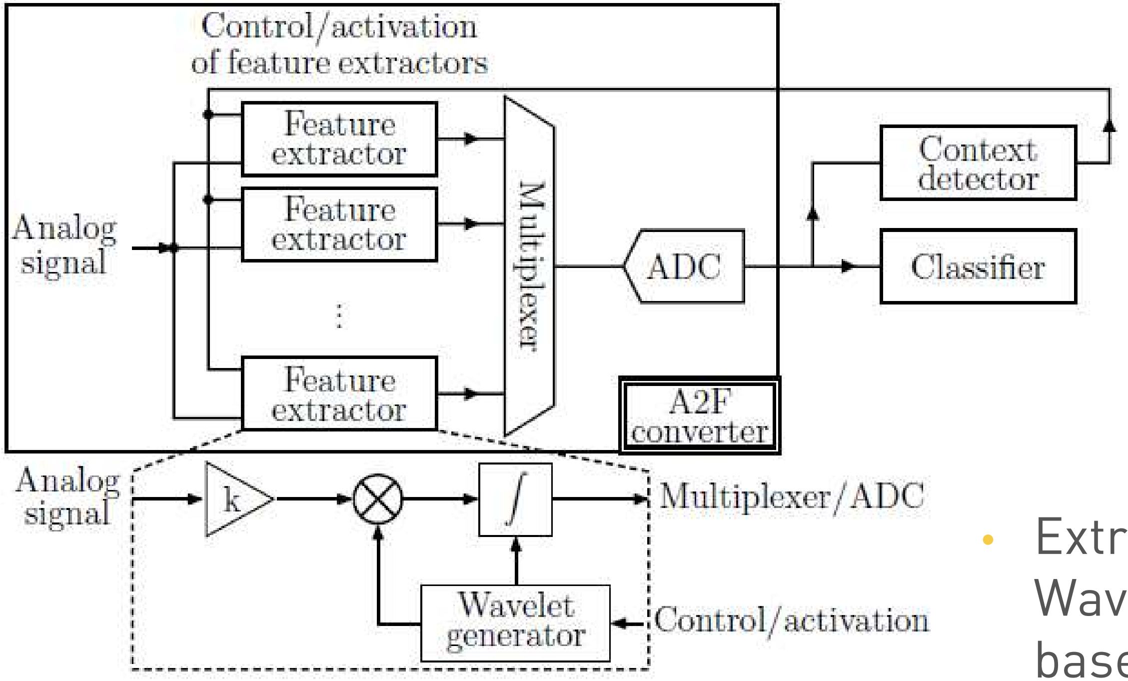
Advantages

- Do not relies on signal sparsity
- Can achieve higher data reduction
- Joint optimization of chosen features and Machine Learning model training
- Generic architecture for different type of signals

Presentation summary

1. Wireless Sensor networks
2. Analog-to-Feature Conversion
   - System architecture
   - Feature selection
3. Application to ECG and Human Activity Recognition
4. Conclusion and Future Work

Reconfigurable System Architecture



- Extraction of the Non-Uniform Wavelet Sampling [5] (NUWS)-based analog domain features
- Analog-to-digital conversion
- Application-specific binary or multiclass classification
- Context detection

Non-Uniform Wavelet Sampling

NUWS : Acquire a small subset of coefficients from wavelet transform.

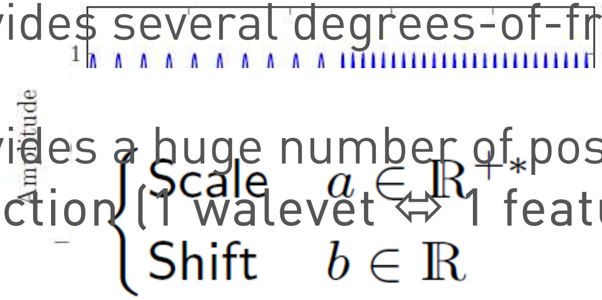
$$Wf(a,b) = \int_{\mathbb{R}} f(t).\psi^*_{a,b}(t)\,dt \qquad \forall t \in \mathbb{R}, \psi_{a,b}(t) = \frac{1}{\sqrt{a}}.\psi\left(\frac{t-b}{a}\right)$$

where $Wf(a,b)$ is the wavelet transform of $f(t)$, $\psi_{a,b}(t)$ is a scaled and shifted wavelet and $\psi(t)$ is the mother wavelet.

✔ Provides information in time and frequency domains

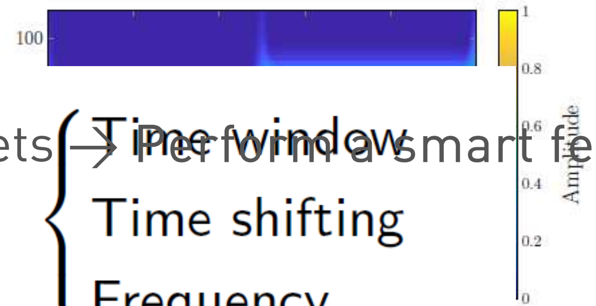
✔ Provides several degrees-of-freedom

✘ Provides a huge number of possible wavelets → Perform a smart features selection (1 walevet ⇔ 1 feature)



Temporal representation

$\left\{ \begin{array}{ll} \text{Scale} & a \in \mathbb{R}^{+*} \\ \text{Shift} & b \in \mathbb{R} \end{array} \right. \longrightarrow \left\{ \begin{array}{l} \text{Time window} \\ \text{Time shifting} \\ \text{Frequency} \end{array} \right.$



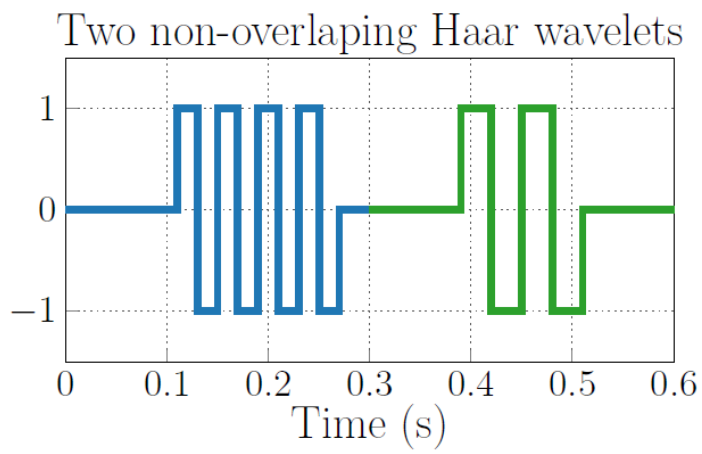
3D Wavelet transform

Feature Selection

Sequential Forward Search (SFS) : successively adding the locally best feature in the set.

SFS scale in !Number of features:

- Use pre-selection method
- Based on Information Gain
- Reduce feature set to 100 best features



3 types of SFS

- Basic SFS
  - Maximize classification accuracy
- Adapted SFS
  - each extractor can extract multiple non-overlaping features
  - limits the maximum number of parallel extractors $nExt_{max}$
- Optimized SFS
  - also accounts for the energetic cost during feature extraction
  - based on estimated power consumption

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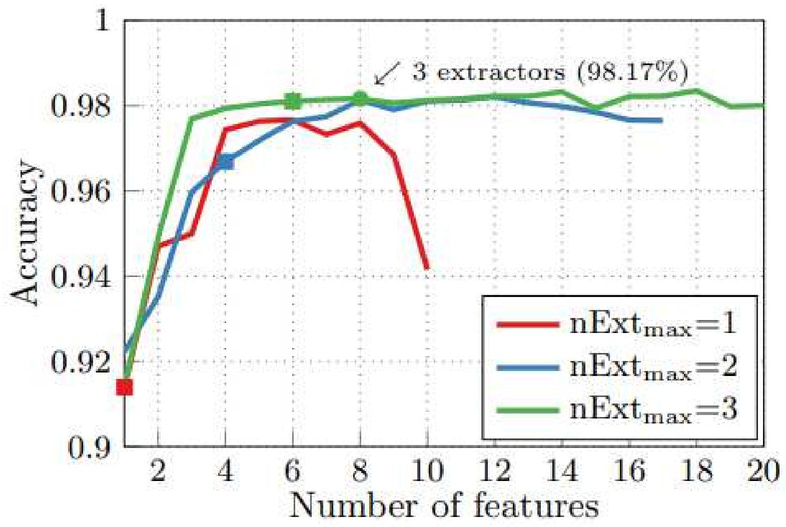
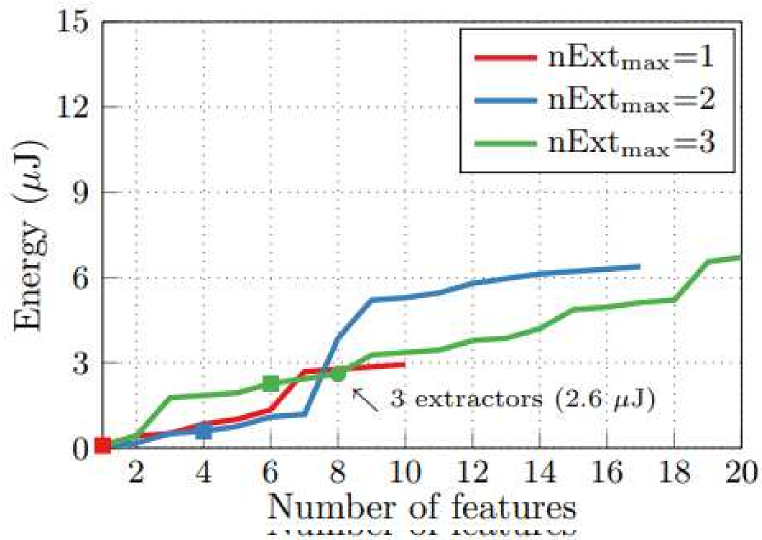
Database presentation

Application	Arrhythmia detection
Dataset (signals)	MIT-BIH Arrhythmia [6] (single channel from 48 ECG recordings of 30 min each, sampled at 360 Hz)
Classes	2 (normal, abnormal)
Initial feature number (Haar wavelets)	502
Type of learning	supervised learning, 70/30% proportion between training and test sets
Analysis window	256 samples of one annotated heartbeat segment (R-peak located at 100th sample) ⇒ 0.711 s

Application for ECG classification

- Adapted vs Optimized SFS
- Neural Network : feedforward with 1 hidden layer (10 neurons)





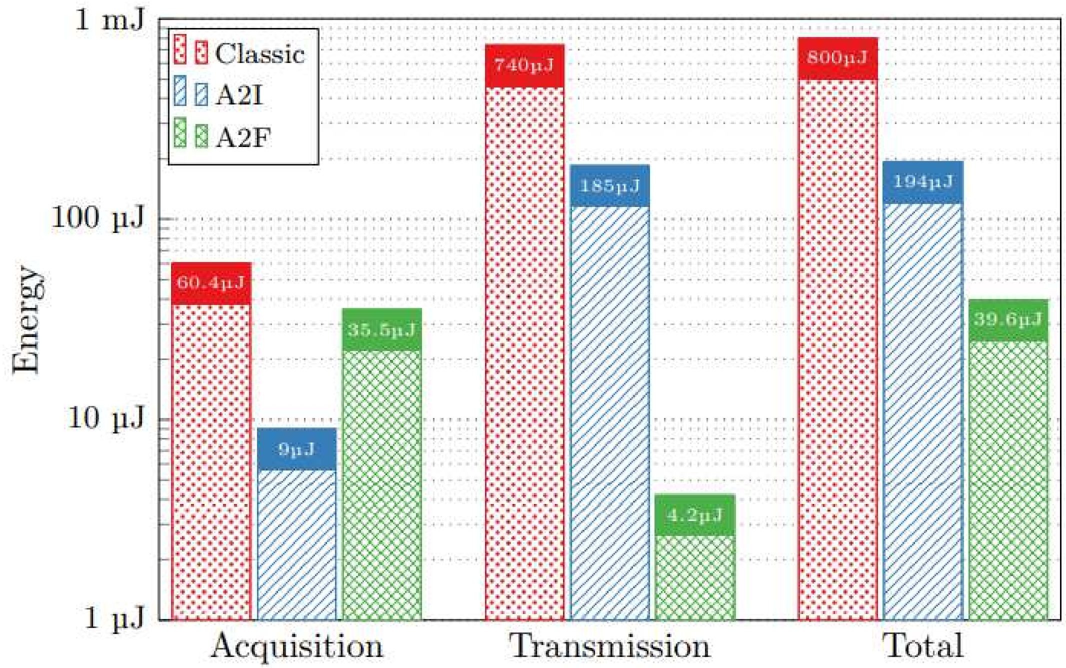
Only require 7 or 8 features from 3 extractors

⇩

Compression ratio: 53 vs 4 for compressed sensing

Energy comparison

- Acquisition and transmission of a 10s signal



A2F is a good and promising method to allow low-power communication and reduce bandwidth

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Conclusion and future work

- IoT brings new challenges with many small connected devices
- A2F as a solution to reduce power and bandwidth of smart IoT sensors
- Generic and reconfigurable architecture to perform A2F conversion

- Future work
  - Circuit design of the full converter ➡ Refine selection with optimized SFS
  - Chip fabrication ➡ Physical measurement of power consumption
  - Application to other applications (EEG, EMG, spectrum sensing ...)

References

[1] T. Chen *et al* . Design of a Low-Power On-Body ECG Classifier for Remote Cardiovascular Monitoring Systems. IEEE Journal on Emerging and Selected Topics in Circuits and Systems, March 2013

[2] L. Yan *et al*. A 0.5- V 12- W Wirelessly Powered Patch-Type Healthcare Sensor for Wearable Body Sensor Network. IEEE Journal of Solid-State Circuits, November 2010.

[3] A. C. W. Wong *et al*. A 1 V 5 mA Multimode IEEE 802.15.6/Bluetooth Low-Energy WBAN Transceiver for Biotelemetry Applications. IEEE Journal of Solid-State Circuits, January 2013.

[4] D. Gangopadhyay *et al*. Compressed Sensing Analog Front-End for Bio-Sensor Applications. IEEE Journal of Solid-State Circuits February 2014.

[5] M. Pelissier and C. Studer, "Non-uniform wavelet sampling for RF Analog-to-Information conversion," IEEE Transactions on Circuits and Systems I: Regular Papers, vol. 65, no. 2, pp. 471–484, 2018.

[6] Moody, G.; Mark, R. The impact of the MIT-BIH arrhythmia database. IEEE Engineering in Medicine and Biology Magazine 2001, 20, 45–50. https://doi.org/10.1109/51.932724

[7] Anguita, D.; Ghio, A.; Oneto, L.; Parra, X.; Reyes-Ortiz, J.L. A public domain dataset for human activity recognition using smartphones. In Proceedings of the 21st European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, Bruges, Belgium, 2013; pp. 437–442.

[8] Gao, W.; Zhang, L.; Huang, W.; Min, F.; He, J.; Song, A. Deep Neural Networks for sensor-based human activity recognition using selective kernel convolution. IEEE Transactions on Instrumentation and Measurement 2021, 70, 1–13. https://doi.org/10.1109/ 763 TIM.2021.3102735.