A.I. and human gait analysis

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Medical context: monitoring frailty

- A pre-frail person can return to a robust state.
- A frail state is almost always irreversible. Evolution toward repeated hospitalisations, loss of autonomy and, 5 years later, premature death in nearly 70% of cases.
- In addition, frailty is a predictor of morbidity and mortality after major surgery.

Usual criteria to measure frailty: Fried's criteria.

- cognitive function tests,
- fatigue state,
- walking ability,
- muscle strength,
- weight.

If one or two of these criteria are abnormal, the person is classified as pre-frail; with more than two criteria, the person is classified as frail.

The objective is to monitor frailty over the long run.

Medical context: clinical constraints

Monitored population.

- Ederly (from nursing home)
- Orthopedic pathologies (lower limb osteoarthrosis cruciate ligament injury, etc.)
- Neurological pathology (stroke, Parkinson's disease, neuropathy, etc.)

Constraints on the data processing.

- Non-intrusive or burdening for the patients or the clinicians (no camera or image)
- Instantaneous feedback to medical doctors
- Interpretable
- Integrate well with the daily routine

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Adopted approach

General methodology.

- Collect multimodal data from a variety of sources:
  - answers to questionnaires,
  - movements from several well-known physical tests (Timed Up and Go, Romberg, etc.).
- Merge those composite data and compute intra- and inter-individual standards.
- Score the frailty state.

In this session, we will focus on **gait analysis**.

- This complex mechanism can be altered by a wide range of pathologies (such as Parkinson's disease, arthritis, stroke, etc.).
- Degraded walk results in a significant loss of autonomy and an increased risk of fall.

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Clinical protocol

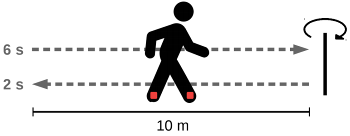
Subjects undergo a fixed protocol:

- Standing,
- Walk forward (10m),
- Turn around,
- Walk back (10m),
- Standing.

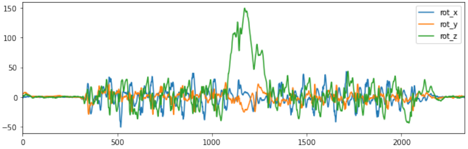
Data are collected with Inertial Measurement Units (IMU), composed of accelerometers, gyroscopes and magnetometers:

- low-cost,
- no need for a dedicated room,
- easy to handle in day-to-day clinical situations.

Protocol schema



Angular velocity (lower back sensor, sampling 100 Hz)



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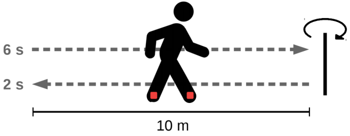

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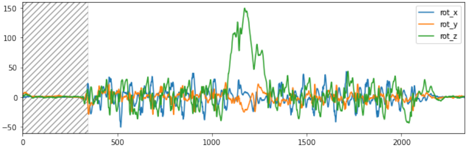

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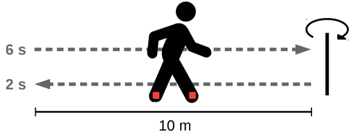

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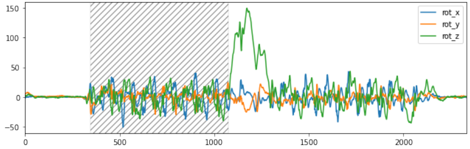

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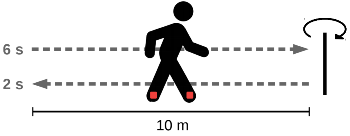

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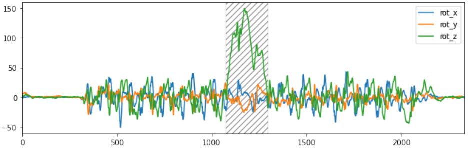

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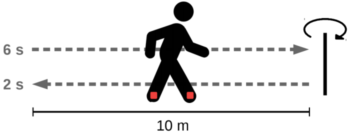

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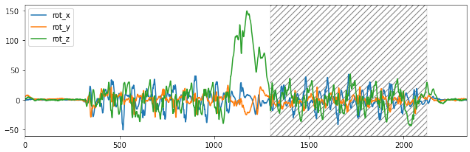

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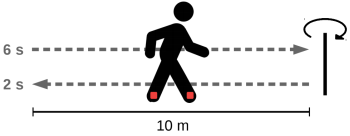

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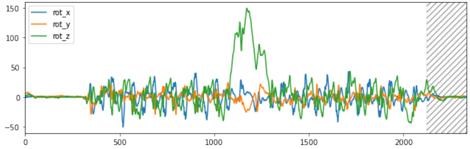
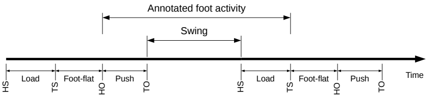


Footsteps, at the core of locomotion

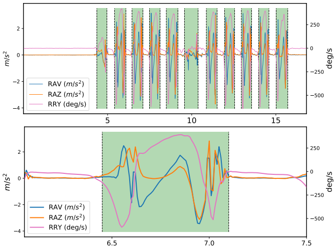
- In many studies, features related to footsteps (step duration, length, symmetry between feet, etc.) are the most important to quantify a pathology.
- Footsteps are the core atoms of locomotion.



Medical definition of a gait cycle.

HS, TS, HO and TO stand for heel-strike, toe-strike,heel-off and toe-off.

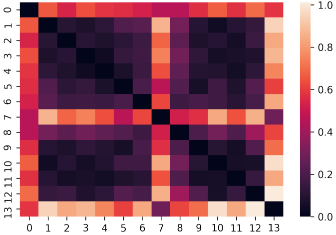
- This complex mechanism can be altered by a wide range of pathologies (such as Parkinson's disease, arthritis, stroke, etc.).
- Degraded walk results in a significant loss of autonomy and an increased risk of fall.



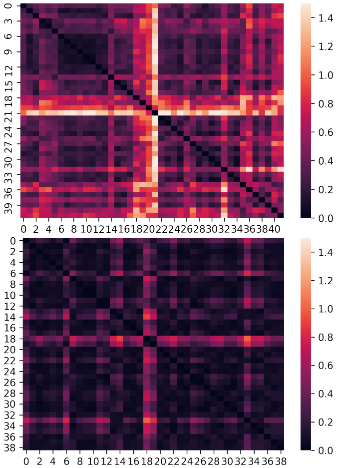
Signal example with foot activity annotations (here, right foot). (Top) Vertical acceleration (RAV), the Z-axis acceleration (RAZ) and the Y-axis angular velocity (RRY) are shown. (Bottom) A close-upon a single foot movement.

Represent the gait: the locogram

- The locogram is a visual tool to assess the gait of a patient.
- It is relies on the step detection.
- All pairwise correlation distances between steps are computed in a distance matrix.



Locogram of an healthy subject (left foot).



Locogram of an neurologically impaired patient.

(Top) Left foot. (Bottom) Right foot.

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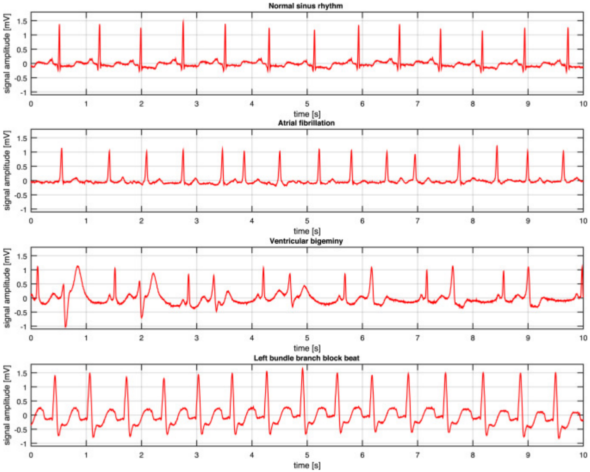
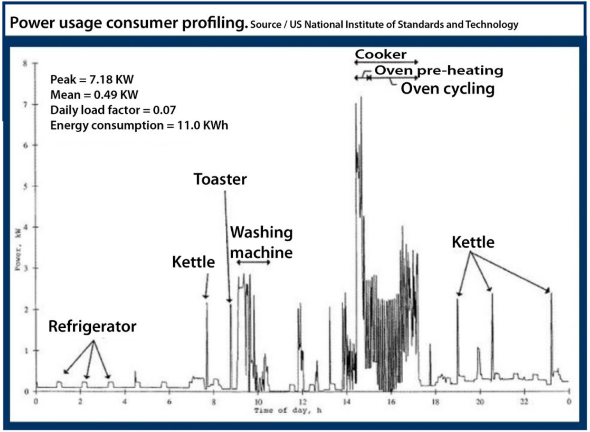
Pattern detection: motivations



ECG signal

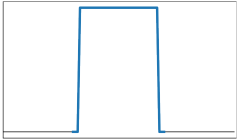
Pattern detection: motivations



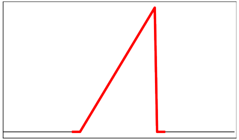
Power consumption

Pattern detection: schematic view

Given a dictionary of two atoms:

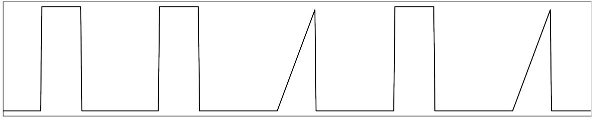


Atom 1



Atom 2

Find where the atoms occur in a signal:



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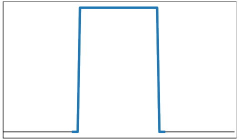

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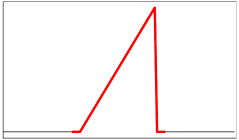

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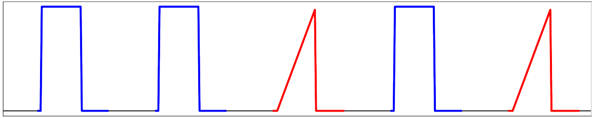


Pattern detection: problem statement

Pattern detection

Given a dictionary of patterns $\mathcal{P}$, retrieve these patterns in an input time serie x.

- The templates and time series can be multivariate.
- The templates in $\mathcal{P}$ can have different lengths.
- The templates can be annotated, i.e. be linked to a specific phenomenon of interest: in this context, pattern recognition will provide an automated annotation of the input time series.

Pattern detection: convolutional representation

We can model the N-sample-long signal $\mathbf{x}$ as a sparse combination of patterns/atoms.

Formally, let $\mathbf{d}_k$ ($k = 1, \ldots, K$) be K patterns of length L.

These patterns can be activated: activations $\mathbf{z}_k$ of length $N - L + 1$

$$\mathbf{z}_k[n] \neq 0 \text{ if pattern } \mathbf{d}_k \text{ is activated at time } n.$$

or, alternatively:

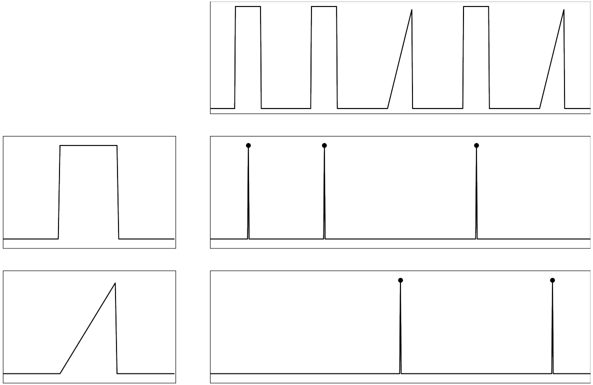
$$\mathbf{x}[n] = \sum_{k=1}^{K} (\mathbf{z}_k \star \mathbf{z}_k)[n] + e[n].$$

Pattern detection: convolutional representation

Model

$$\mathbf{x}[n] = \sum_{k=1}^{K} (\mathbf{z}_k \star \mathbf{d}_k)[n] + e[n].$$

Illustrative example



Pattern detection: optimization problem

The optimization problem to find the activations is:

$$\mathbf{Z}^{\star} = \arg\min_{(\mathbf{z}_k)} \left\| \mathbf{x} - \sum_{k=1}^{K} (\mathbf{z}_k \star \mathbf{d}_k) \right\|_2^2 \quad + \quad \lambda \sum_{k=1}^{K} \|\mathbf{z}_k\|_1$$

- **Sparsity constraint** for the activations $\mathbf{z}_k$, that improves the interpretability of the learned patterns.
- **Convex problem**, so several methods exist to solve it (ISTA, ADMM, FISTA, CD, etc.)

This task is called **convolutional sparse coding**.

Conclusion

Time to code!