Détection d'événements à partir de capteurs sols – application au suivi de personnes fragiles

Soutenance de thèse

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Thèse industrielle entre l'ENS Paris-Saclay et Tarkett

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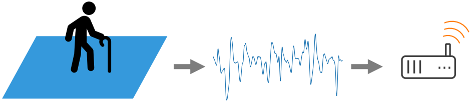
Introduction

Context

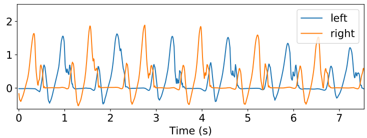
- Elderly population is growing
- Higher levels of frailty globally
- Increasing demand for reliable monitoring devices
- Tarkett, French company with 12,500 employees, 13 industrial sites, sells 1.3 millions m^2 of flooring every day
- *Floor in Motion*: a floor-based sensor for elderly care
- **Objective**: providing tools for elderly monitoring in nursing homes
  - First aimed application: fall detection



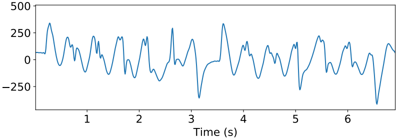
Introduction

Motivation

- Processing and understanding time series
  - Proliferation of sensor-based systems
  - Redundancy, interpretability, external pertubations
- Real world application
  - Real-time processing in a limited system
  - Convenient hypotheses not granted



Foot-attached accelerometer



Tarkett’s floor sensor

A tour of monitoring systems

Systems

What makes a good monitoring system ?

- coverage and occlusion
- intrusiveness
- signal quality / information
- robustness
- ease of installation / use
- scalability

Criteria
Coverage/Occlusion
Intrusiveness
Signal quality / info
Robustness
Ease of instal. / use
Scalability

A tour of monitoring systems

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What makes a good monitoring system ?

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Signal acquisition

Vision

RGB-Camera
Omni-Camera
Depth-Camera

Criteria	RGB cam	Depth cam
Coverage/Occlusion	★☆☆	★☆☆
Intrusiveness	★☆☆	★☆☆
Signal quality / info	★★★	★★★
Robustness	★★☆	★★★
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A tour of monitoring systems

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What makes a good monitoring system ?

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Signal acquisition	
Vision	**Wearable**
RGB-Camera Omni-Camera Depth-Camera	Accelerometer Gyroscope Barometric pressure

Criteria	RGB cam	Depth cam	Wearable
Coverage/Occlusion	★☆☆	★☆☆	★★★
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A tour of monitoring systems

Systems

What makes a good monitoring system ?

- coverage and occlusion
- intrusiveness
- signal quality / information
- robustness
- ease of installation / use
- scalability

Signal acquisition		
Vision	**Wearable**	**Ambient**
RGB-Camera Omni-Camera Depth-Camera	Accelerometer Gyroscope Barometric pressure	Microphone Radar Wi-Fi Vibrational Pressure

Criteria	RGB cam	Depth cam	Wearable	Acoustic	Radar / Wi-Fi	Vibration	Floor
Coverage/Occlusion	★☆☆	★☆☆	★★★	★★☆	★☆☆	★★★	★★★
Intrusiveness	★☆☆	★☆☆	★★☆	★☆☆	★★☆	★★★	★★★
Signal quality / info	★★★	★★★	★★☆	★★☆	★☆☆	★★☆	★★☆
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Scalability	★☆☆	★☆☆	★★★	★★☆	★☆☆	★★☆	★★★

A tour of monitoring systems

Information extraction

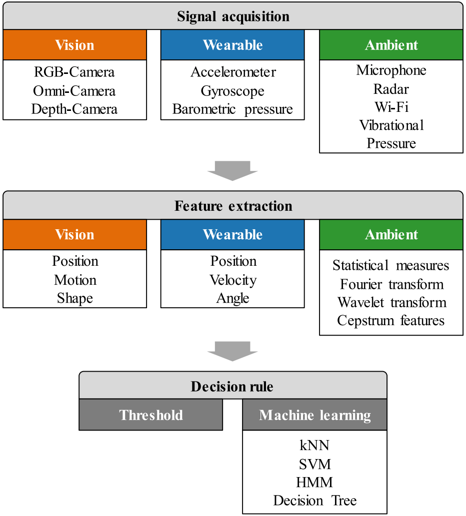
How to process the inputs ?

- All systems use feature extraction
- The "level" of feature engineering depends on the complexity / dimensionality of the input signal

How to deal with processed signals ?

Time series classification

1. Series as *sequences*
   - Distance-based methods
2. Series as *feature vectors*
   - Computing several measures over a fixed size
   - Classification models (Anomaly detection, classical supervised models...)



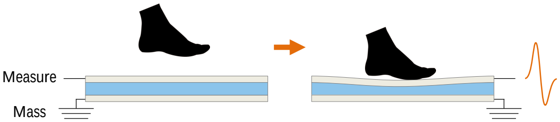
A tour of monitoring systems

Tarkett sensor

- Piezoelectric principle:

$$d = \frac{Q}{F},$$

(simple version) with d the *piezoelectric constant*.
When stressed or squeezed, the material emits charges.



A tour of monitoring systems

Tarkett sensor

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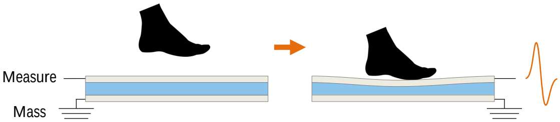
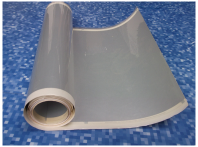
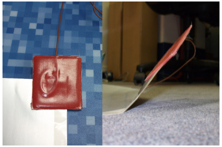
When stressed or squeezed, the material emits charges.

- How does this look like ?
0.3 mm thick and 60 cm wide roll with customizable length




Roll of sensor


Connector

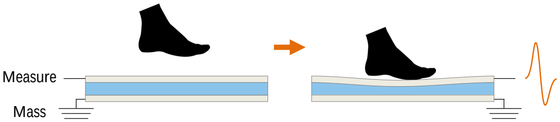
A tour of monitoring systems

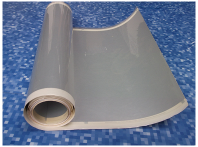
Tarkett sensor

- Piezoelectric principle:

  $$d = \frac{Q}{F},$$

  (simple version) with d the *piezoelectric constant*.
  When stressed or squeezed, the material emits charges.
- How does this look like ?
  0.3 mm thick and 60 cm wide roll with customizable length
- How is it installed ?
  - Under the flooring
  - Several connected bands for each area, hence one area corresponds to one input





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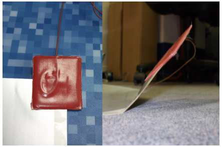
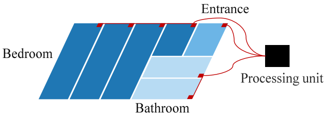


Connector

Sensor set up



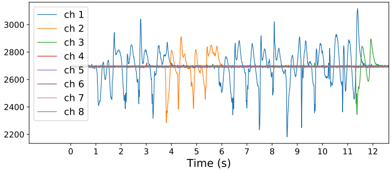
Room equipped with the system

Fall detection

Data

Preprocessing

- linear detrending
- low-pass filtering
- zeroing low energy channels
- sum over all channels



Fall detection

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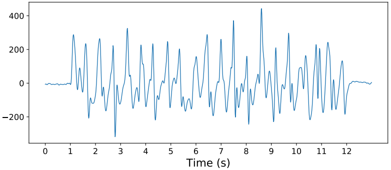

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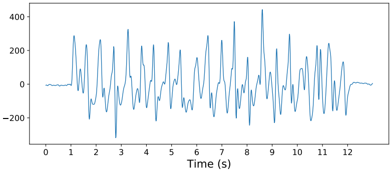
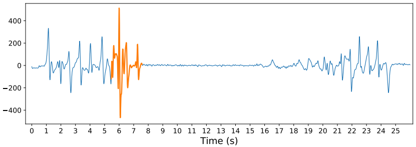
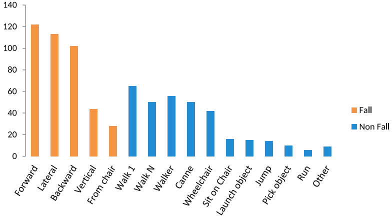


Experimental dataset

- 742 signals
- 55% *fall*, 45% *non-fall*
- varied fall events (forward, backward...) and activities of daily living (walking, sitting...)



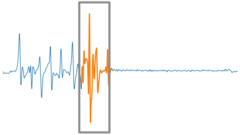


Fall detection

Method

Time series as *feature vector*. At every timestamp:

1. Window over the signal: 2.5 s
2. Compute feature vector: 29 statistical measures (Min, Max, Shannon energy, Percentile,...) over three representations of the signal



$$s \quad \frac{d}{dt}s \quad \mathcal{F}(s)$$

$$\underbrace{\text{Min, Max, Energy...}}_{\mathbf{x} \in \mathbb{R}^{87}}$$

3. Classification model: Random Forest [Breiman, 2001]

Random Forest: Aggregation of N_T **decision trees**.

Decision tree

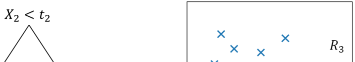
Feature space $\mathcal{X} = \mathbb{R}^Q$. Division of $\mathcal{X}$ into non-overlapping regions $R_1, \ldots, R_J$. Algorithm CART that use recursive binary splits [Breiman et al., 1984]

$$\arg\min_{X_q, \tau} \mathrm{IG}$$

$$\mathrm{IG}(X_q, \tau) = I(n) - \frac{N_l}{N_n} I(l) - \frac{N_r}{N_n} I(r)$$

$$I(n) = \mathrm{Gini}(n) = \sum_k p_{nk}(1 - p_{nk})$$

$$f(x) = \sum_{j=1}^{J} c_j \mathbb{1}(x \in R_j)$$



Fall detection

Learning

Model-based transfer learning

Introduction

- **Issue**: one-dimensional signals for large areas
- Goal: Classify elderly from other individuals
  - Most signals are made of walks of staff individuals
- **Subtask**: Bring the model's attention over step-related signals
- A model to recognize steps ?

Introduction

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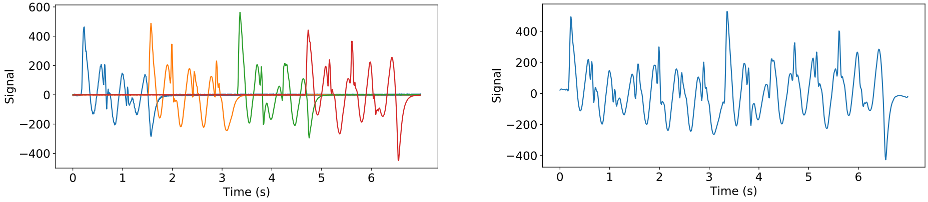


(a) Raw signal (b) Preprocessed signal

Figure: Healthy individual walking on the sensor.

- Signals are complex
- How to **localize** steps ?
- **This presentation:** A step detector using convolutional neural network: Step Proposal Network

Region proposal network

Object detection

- Classification: What is the image class ?

Figure: Classification vs Object detection. Source: [Girshick et al., 2014], [Ren et al., 2015]

Region proposal network

Object detection

- Classification: What is the image class ?
- Object detection: Where are the objects and what are they classes ?

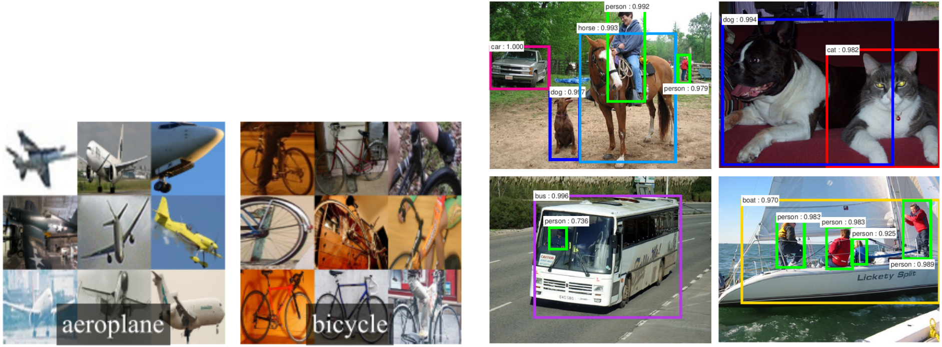
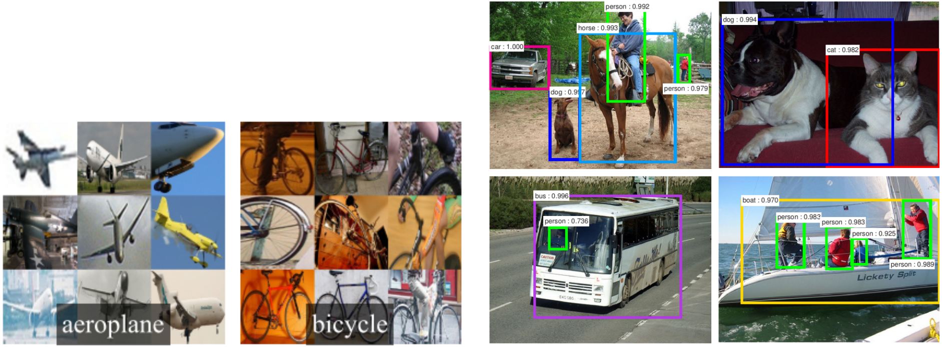


Figure: Classification vs Object detection. Source: [Girshick et al., 2014], [Ren et al., 2015]

Region proposal network

Object detection

- Classification: What is the image class ?
- Object detection: Where are the objects and what are they classes ?
- How to efficiently localize objects ?
- Proposal models [Hosang et al., 2016]
- Faster R-CNN [Ren et al., 2015]



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Region proposal network

Faster R-CNN

- Main idea: proposals are generated by a CNN called Region Proposal Network

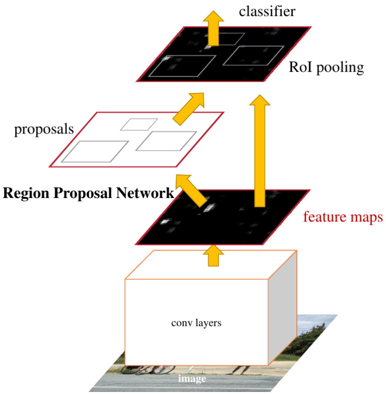

Figure: Region proposal network. Source: [Ren et al., 2015]

Region proposal network

Faster R-CNN

- Main idea: proposals are generated by a CNN called Region Proposal Network
- A sliding window is passed: multiple *anchors* over each location (various sizes and scales)
- Two layers: Classification (Object / Not Object) and Regression (anchor coordinates)

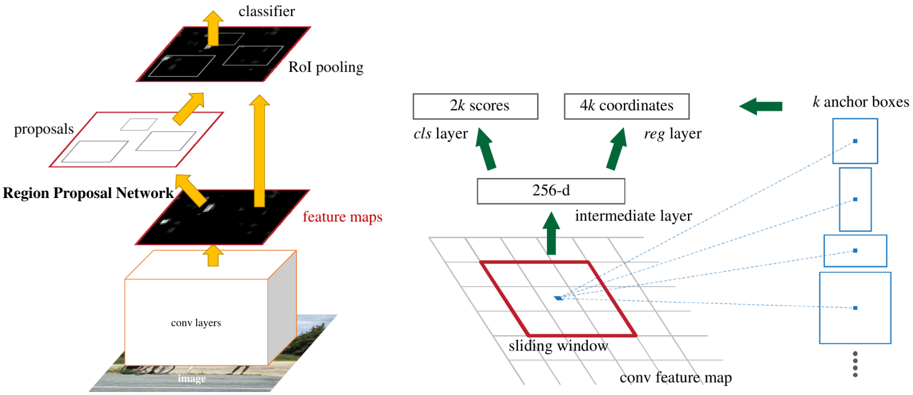

Figure: Region proposal network. Source: [Ren et al., 2015]

Step proposal network

Main architecture

- Directly inspired from RPN
- Simple architecture with three hidden layers, all **convolutional**
- Output: probability of having a step at a specific window location and size
  - Here 3 sizes and all discrete locations are considered

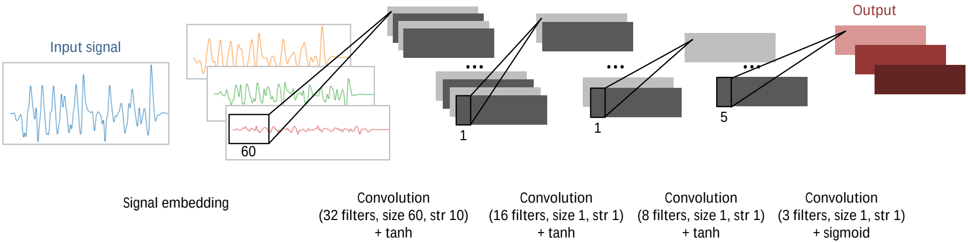

Figure: Architecture of SPN .

Step proposal network

Main architecture

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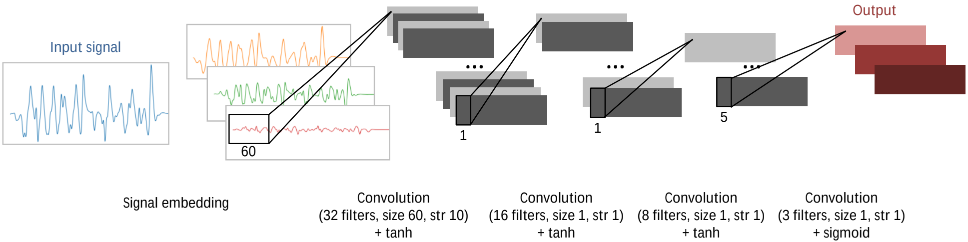

Figure: Architecture of SPN .

- Use the convolutional representation to “boost” training
- First layer (Signal embedding) of SPN is trained **separately** using convolutional dictionary learning

Signal embedding

Convolutional dictionary learning

- $\mathbf{s}$: data to be represented
- Objective : find M atoms $\mathbf{d}_m$ and activation signals $\mathbf{x}_m$ such that

$$\mathbf{s} \approx \sum_{m=1}^{M} \mathbf{x}_m * \mathbf{d}_m$$

- $*$: convolution

Signal embedding

Convolutional dictionary learning

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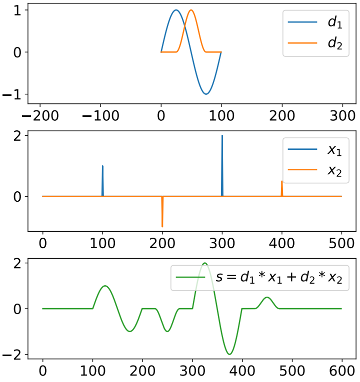

Figure: Convolutional dictionary learning.

Signal embedding

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- $*$: convolution

CDL general problem:

$$\underset{\mathbf{x}_m, \mathbf{d}_m}{\arg\min} \ \frac{1}{2} \left\| \sum_{m=1}^{M} \mathbf{x}_m * \mathbf{d}_m - \mathbf{s} \right\|_2^2 + \lambda \sum_{m=1}^{M} \|\mathbf{x}_m\|_1$$

$$\text{s.t.} \quad \|\mathbf{d}_m\|_2 \leq 1 \quad \forall m \, .$$

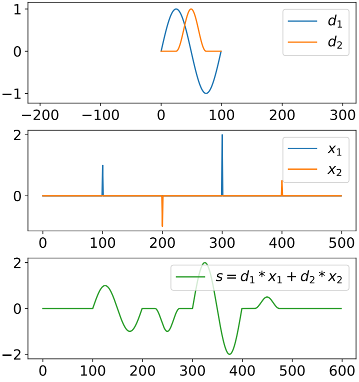

Figure: Convolutional dictionary learning.

Signal embedding

Learning step atoms

- Learning with Alternating Direction Method of Multipliers (ADMM) [Bristow et al., 2013]
- 3 atoms of length 0.7 second

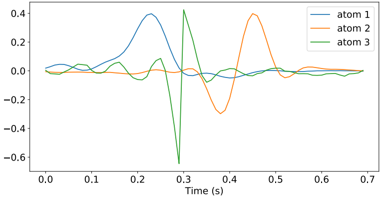

Figure: Dictionary.

Signal embedding

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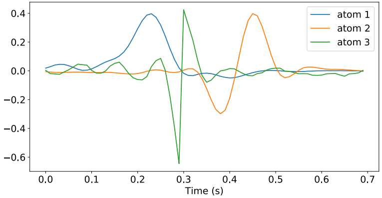

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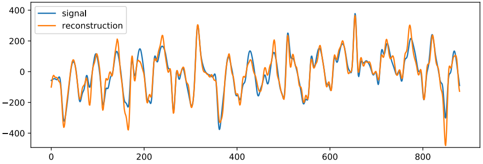
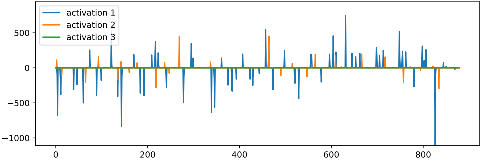


(a) Original signal and its reconstruction



(b) Signal activations

Signal embedding

Learning step atoms

- Learning with Alternating Direction Method of Multipliers (ADMM) [Bristow et al., 2013]
- 3 atoms of length 0.7 second
- Use the following embedding:

$$\mathbf{S} \doteq \left(\mathbf{s} * \mathbf{d}_m\right)_{1 \leq m \leq 3}$$

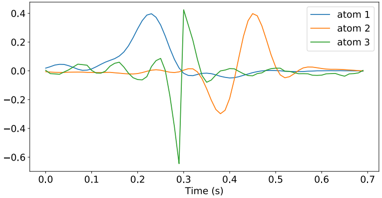
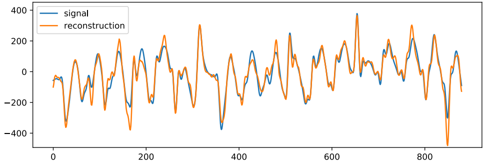


Figure: Dictionary.



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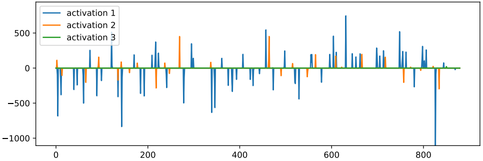
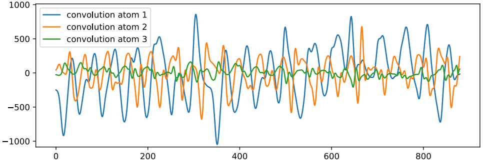


(b) Signal activations



(c) Embedding

Signal embedding

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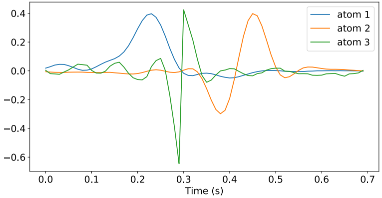

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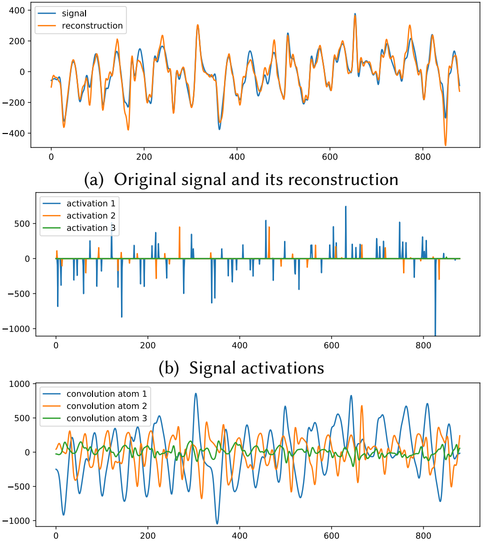


(a) Original signal and its reconstruction

(b) Signal activations

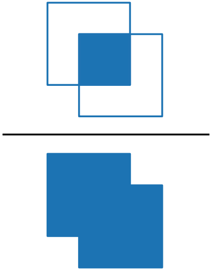
(c) Embedding

Step proposal network

Principle

- Objective of SPN : output boxes with largest Intersection over Union (IoU)
- IoU: $\mathbf{b_j}$ are labelled boxes, $\hat{b}$ is an estimated box:

$$\mathrm{IoU}(\hat{b}) \doteq \max_{j} \frac{|\mathbf{b_j} \cap \hat{b}|}{|\mathbf{b_j} \cup \hat{b}|}$$



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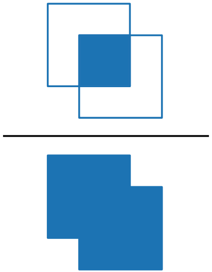

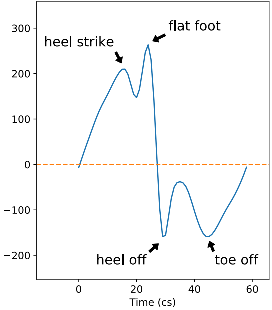

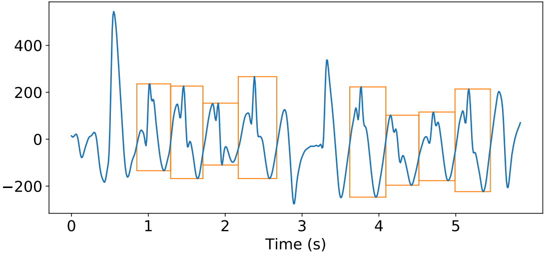

Step proposal network

Training

- Output: a matrix $\mathbf{W} \in \mathbb{R}^{T \times K}$
  - T: signal length
  - K: number of different box sizes
- $\mathbf{W}_{t,k}$: probability that the box b_t^k starting at time t and of size 0.4s, 0.5s, or 0.6s (for respectively $k = 1, 2,$ or 3) has a large IoU score
- Positive boxes: $\mathrm{IoU}(b_t^k) > \sqrt{0.7}$
- Negative boxes: $\mathrm{IoU}(b_t^k) < \sqrt{0.3}$
- Other are not used for training

The loss function $\mathcal{L}$ over a signal $\mathbf{s}$ is defined as:

$$\mathcal{L}(\mathbf{s}, \mathbf{W}) = \sum_{t} \sum_{k \in [1,2,3]} \mathbb{1}_{\mathrm{IoU}(b_t^k) > \sqrt{0.7}} \log(\mathbf{W}_{t,k}) + \mathbb{1}_{\mathrm{IoU}(b_t^k) < \sqrt{0.3}} \log(1 - \mathbf{W}_{t,k}).$$

Results

Data

- 43 signals recorded in a nursing home
- Manually labeled steps

Training

- SPN is trained using classical gradient descent
- Training time: < 5 minutes
- Inference (detection over a 10s signal): < 1 second
- Optimization details
  - learning rate of 10^{-3}
  - learning rate decay ($\times 0.9$ every 10 epochs)
  - Nesterov momentum

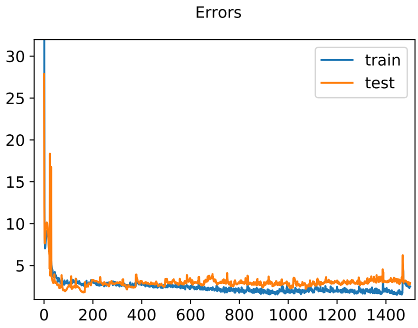

Figure: SPN training and testing errors.

Results

- Object detection use the mean Average Precision (mAP): area under the Precision-Recall curve
- **Without** embedding, mAP = 72,5%
- **With** embedding, mAP = 78,6%

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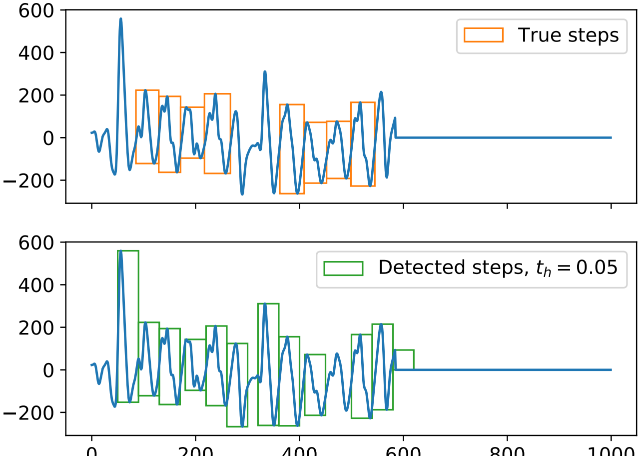

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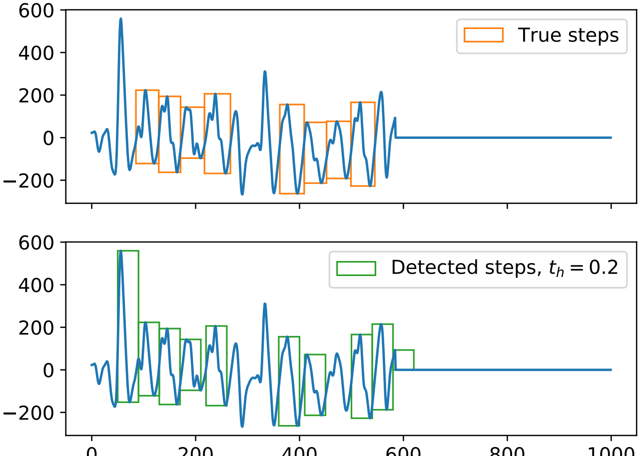

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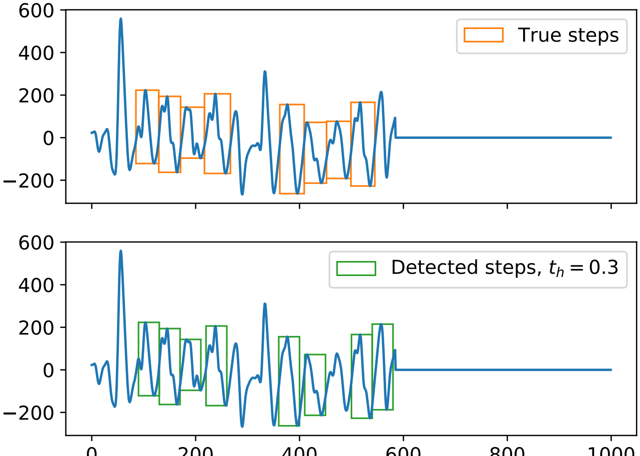

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- SPN uses the convolutional representation to detect steps
- Allows to located steps in complex signals
- Training and inference are fast

Future work

- Add a regression layer on the step proposals
- Tests on step detection benchmarks data sets

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Thanks

Contact: minvielle@cmla.ens-cachan.fr

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