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

Mercredi 15 Juillet 2020

Table of contents

1. Introduction

2. Step proposal network
   - Region proposal network
   - Main architecture
   - Signal embedding
   - Step proposal network
   - Results

3. Conclusion

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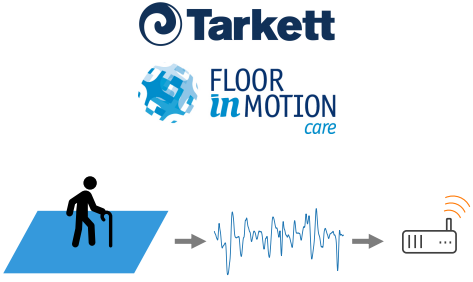
Introduction

Context

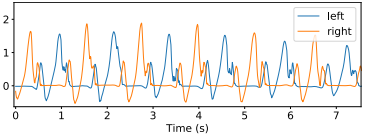
- Elderly population is growing
- Higher levels of frailty globally
- Increasing demand for reliable monitoring devices
- Tarkett, French company with 12,500 employees, 13 industrial sites, sells 1.3 millions m^2 of flooring every day
- *Floor in Motion*: a floor-based sensor for elderly care
- **Objective**: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



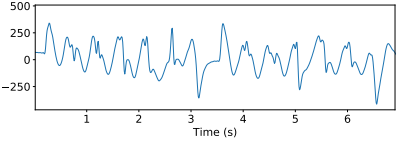
Introduction

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



(a) Foot-attached accelerometer



(b) Tarkett's floor sensor

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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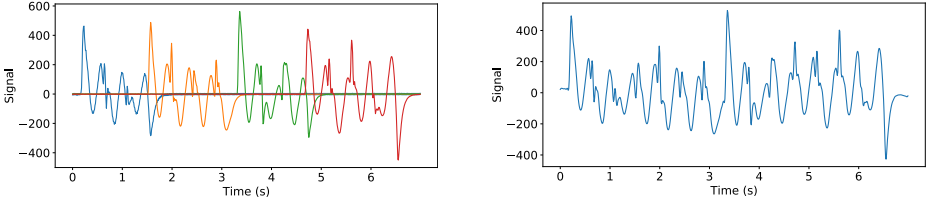
- A model to recognize steps ?



(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

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Region proposal network

Object detection

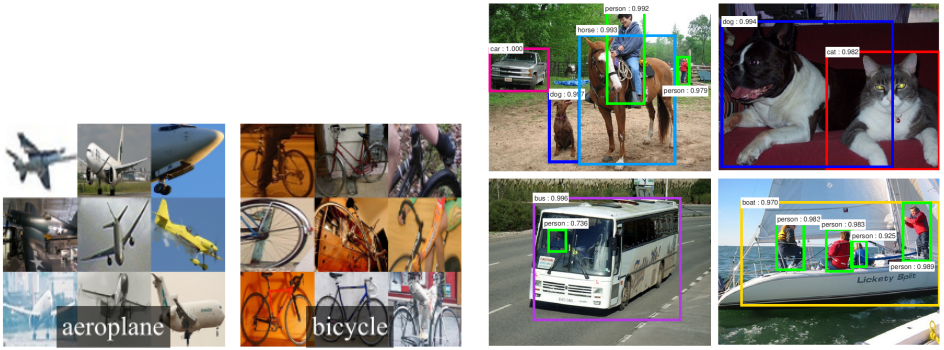
- Classification: What is the image class ?

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 ?



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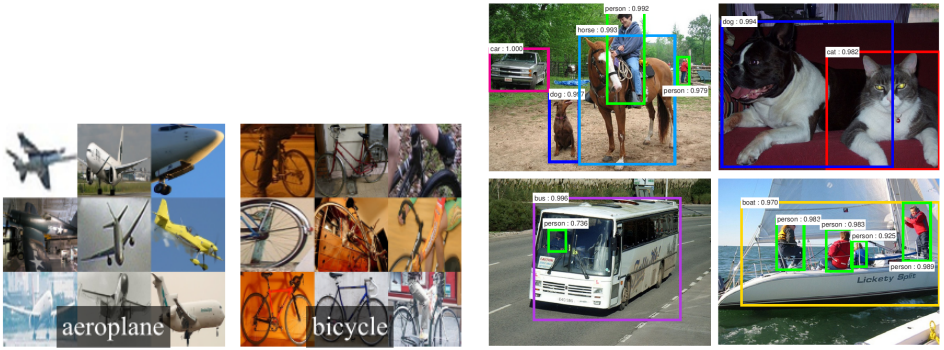
Region proposal network

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

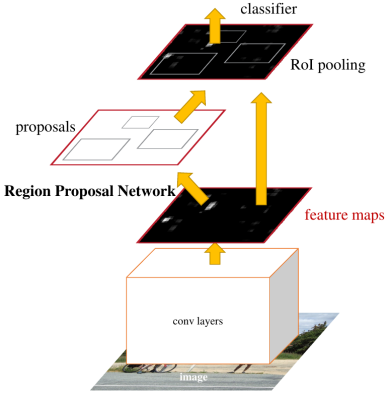
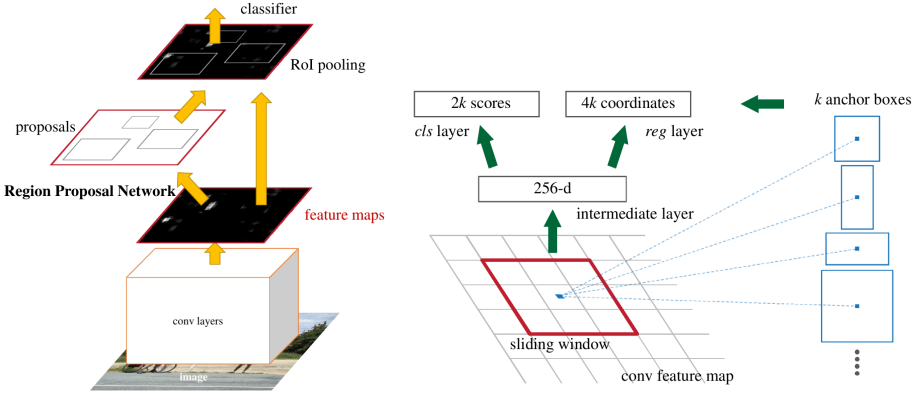


Figure: Region proposal network. Source: [Ren et al., 2015]

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)



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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

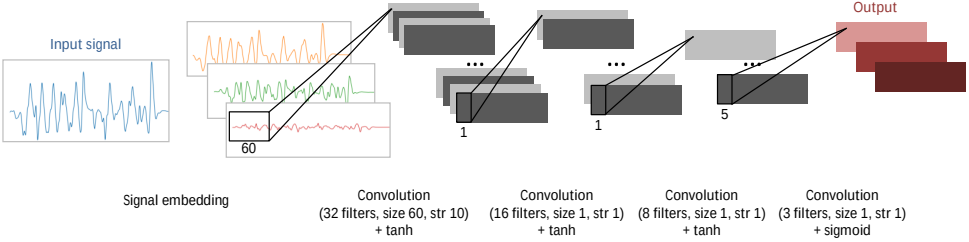

Figure: Architecture of SPN .

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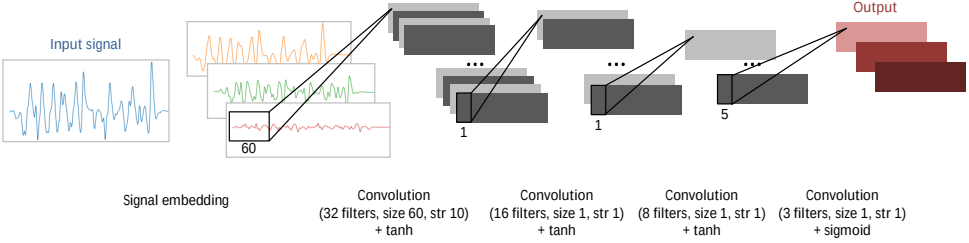

Figure: Architecture of SPN .

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

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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

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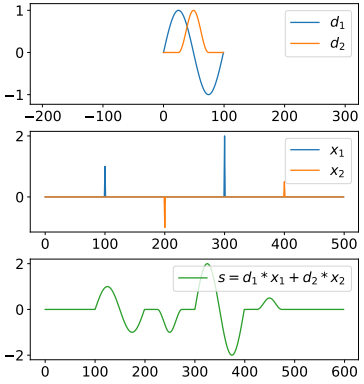

Figure: Convolutional dictionary learning.

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CDL general problem:

$$\arg\min_{\mathbf{x}_m, \mathbf{d}_m} \frac{1}{2} \left\| \sum_{m=1}^{M} \mathbf{x}_m * \mathbf{d}_m - \mathbf{s} \right\|_2^2 + \lambda \sum_{m=1}^{M} \|\mathbf{x}_m\|_1$$
$$\text{s.t.} \quad \|\mathbf{d}_m\|_2 \leq 1 \quad \forall m \, .$$

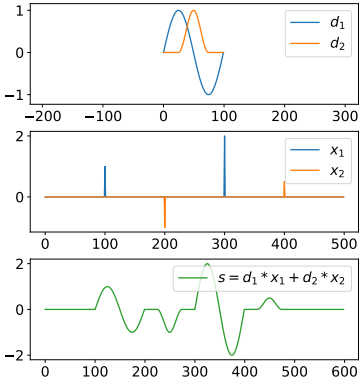

Figure: Convolutional dictionary learning.

Signal embedding

Learning step atoms

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

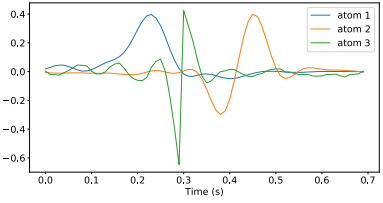

Figure: Dictionary.

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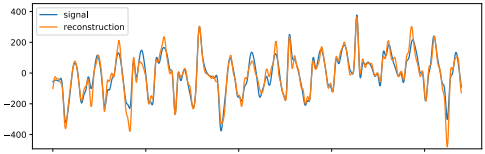
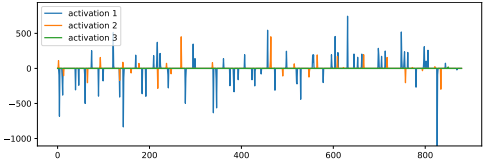
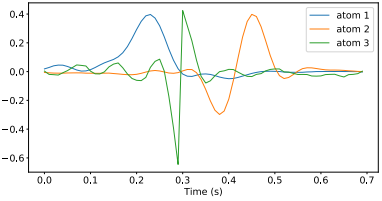


(a) Original signal and its reconstruction



(b) Signal activations



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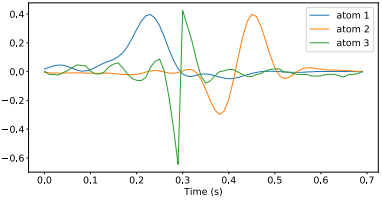

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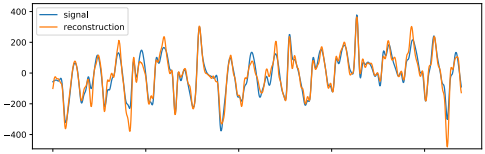

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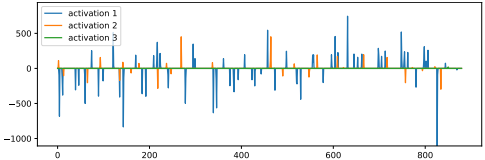

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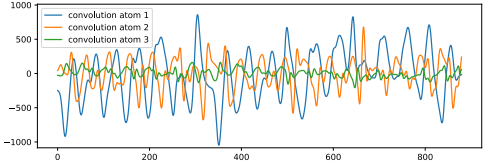

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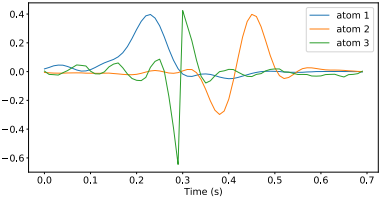

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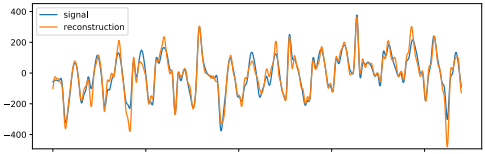

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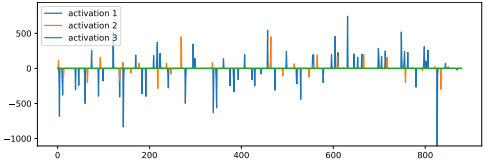

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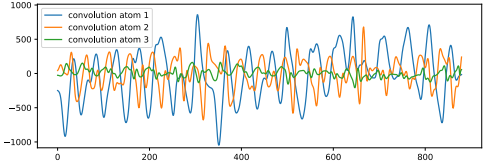

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Step proposal network

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:

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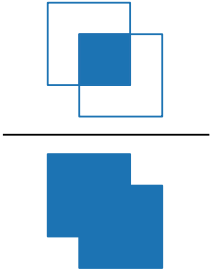

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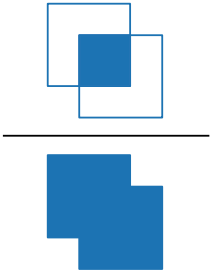

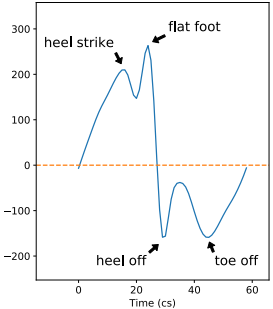

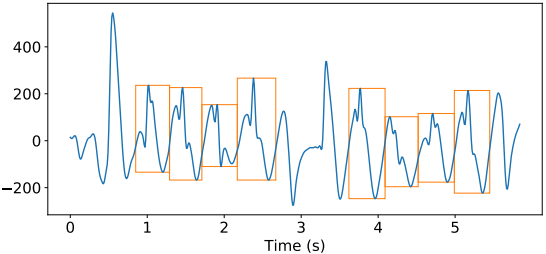

Step proposal network

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:

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

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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

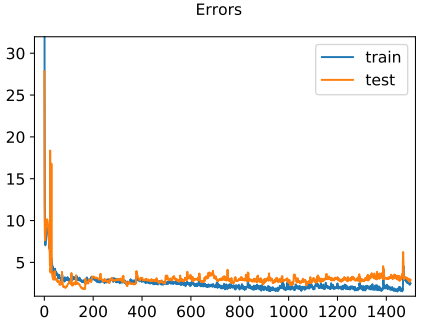

Figure: SPN training and testing errors.

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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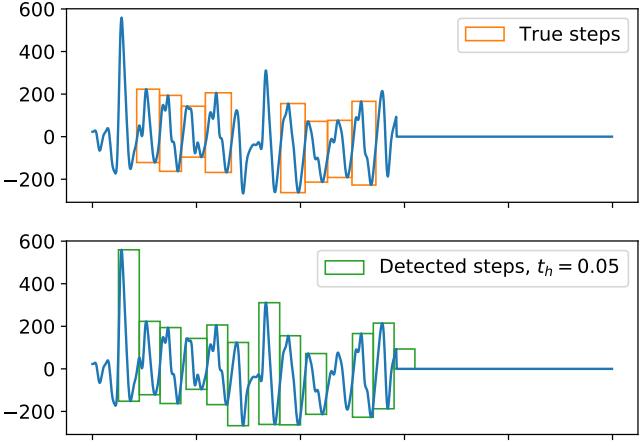

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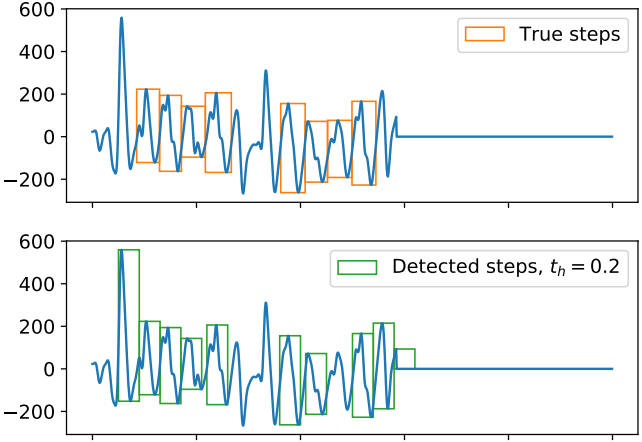

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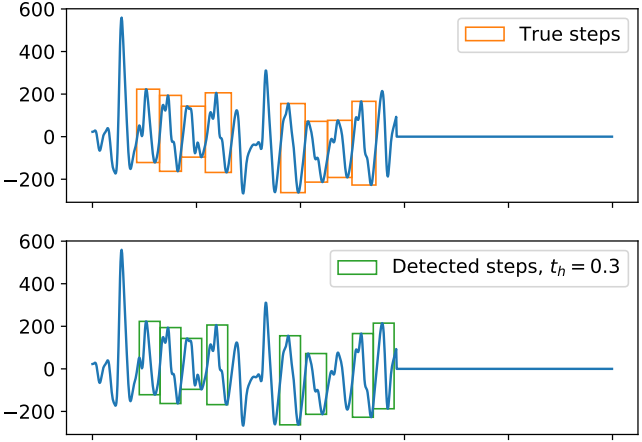

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- SPN uses the convolutional representation to detect steps
- Allows to located steps in complex signals
- Training and inference are fast

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

Reference: L. Minvielle and J. Audiffren. Nursenet : Monitoring elderly levels of activity with a piezoelectric floor. Sensors, 19(18), 2019 link

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