

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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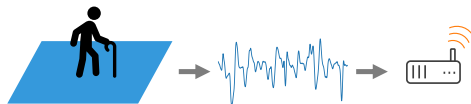
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Introduction

Context

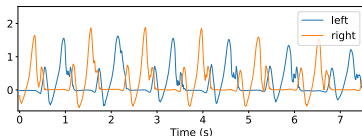
- ▶ Elderly population is growing
- ▶ Higher levels of frailty globally
- ▶ Increasing demand for reliable monitoring devices
- ▶ Tarkett, French company with 12,500 employees, 13 industrial sites, sells 1.3 millions m² of flooring every day
- ▶ *Floor in Motion*: a floor-based sensor for elderly care
- ▶ **Objective**: providing tools for elderly monitoring in nursing homes
 - ▶ First aimed application: fall detection



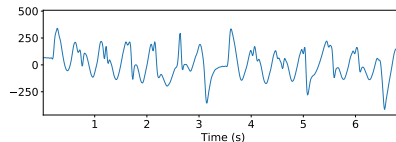
Introduction

Motivation

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



(a) Foot-attached accelerometer



(b) 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

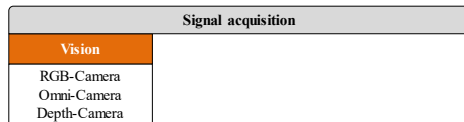
Scalability

A tour of monitoring systems

Systems

What makes a good monitoring system ?

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- ▶ scalability



Criteria	RGB cam	Depth cam
Coverage/Occlusion	★☆☆	★☆☆
Intrusiveness	★☆☆	★☆☆
Signal quality / info	★★★★	★★★★
Robustness	★★★☆☆	★★★★
Ease of instal. / use	★☆☆	★☆☆
Scalability	★☆☆	★☆☆

A tour of monitoring systems

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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	☆☆☆	☆☆☆	★★★
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 ?

- ▶ coverage and occlusion
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- ▶ 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	☆☆☆	☆☆☆	★★★	★★☆	☆☆☆	★★★	★★★
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A tour of monitoring systems

Processing

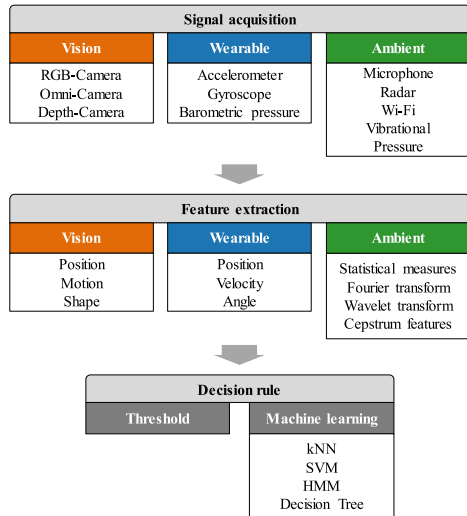
How to process the inputs ?

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

Time series classification

How to deal with

- ▶ Series as sequence
 - ▶ Distance-based methods
- ▶ Series as feature vector
 - ▶ Computing several measures over a fixed size
 - ▶ Classification models
 - ▶ Anomaly detection, classical supervised models...

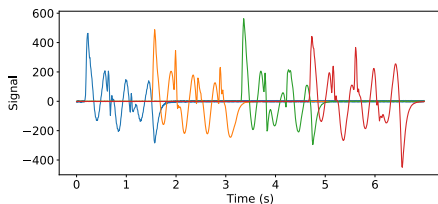


Introduction

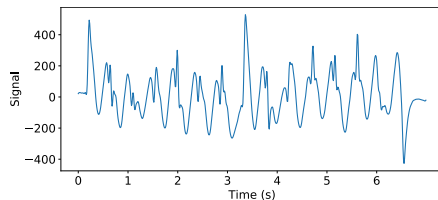
- ▶ **Issue:** one-dimensional signals for large areas
- ▶ **Goal:** Classify elderly from other individuals
 - ▶ Most signals are made of walks of staff individuals
- ▶ **Subtask:** Bring the model's attention over step-related signals
- ▶ A model to recognize steps ?

Introduction

- ▶ **Issue:** one-dimensional signals for large areas
- ▶ **Goal:** Classify elderly from other individuals
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- ▶ **Subtask:** Bring the model's attention over step-related signals
- ▶ 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

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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 ?

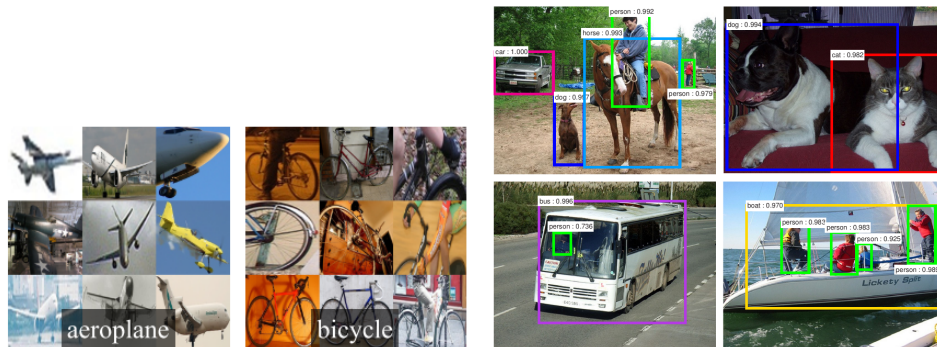


Figure: Classification vs Object detection. Source: [Girshick et al., 2014], [Ren et al., 2015]

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]

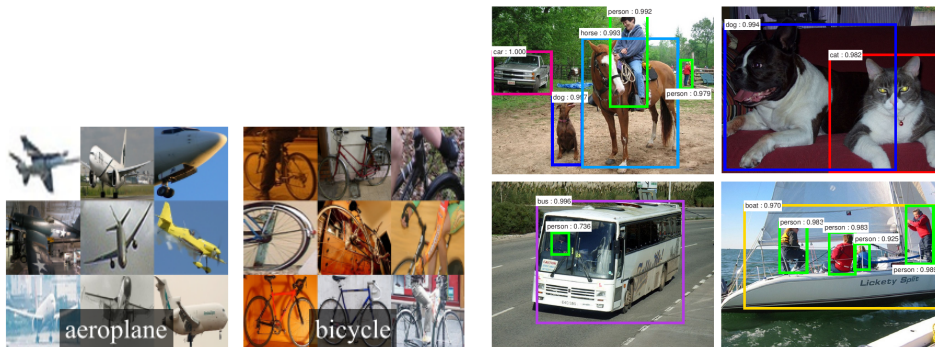


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Region proposal network

Faster R-CNN

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

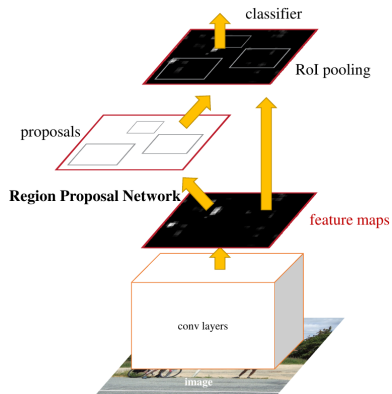


Figure: Region proposal network. Source: [Ren et al., 2015]

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)

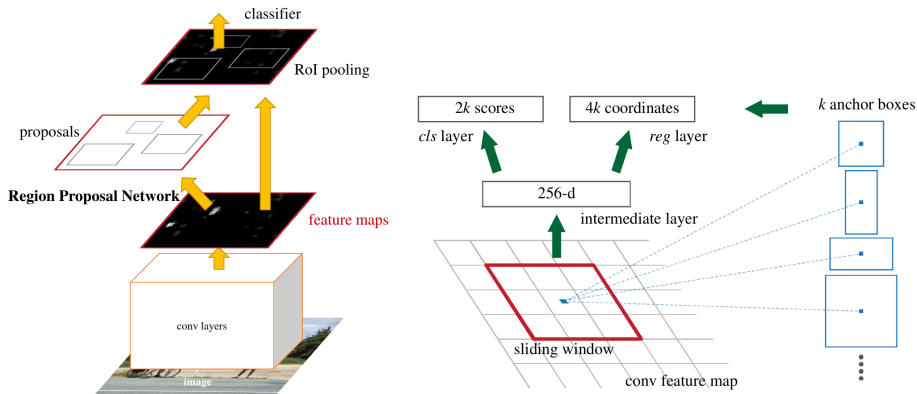


Figure: Region proposal network. Source: [Ren et al., 2015]

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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

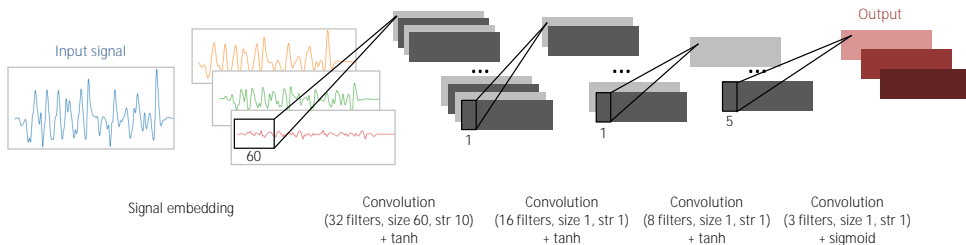


Figure: Architecture of SPN .

Step proposal network

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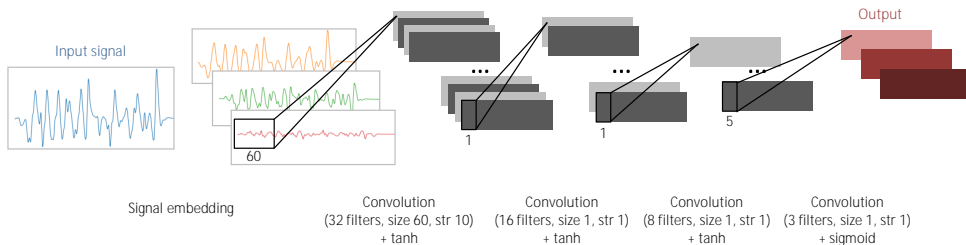


Figure: Architecture of SPN .

- ▶ 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

Signal embedding

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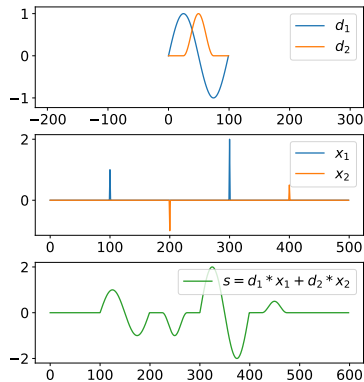


Figure: Convolutional dictionary learning.

Signal embedding

Convolutional dictionary learning

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CDL general problem:

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

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

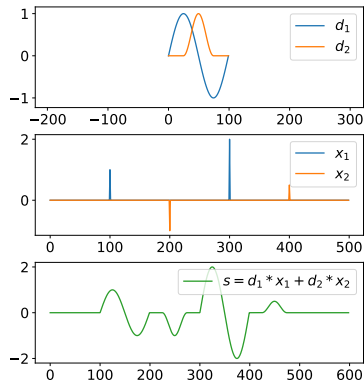


Figure: Convolutional dictionary learning.

Signal embedding

Learning step atoms

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

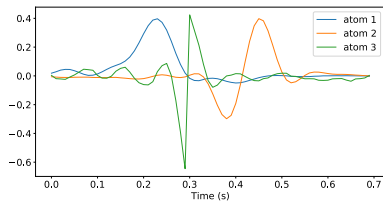


Figure: Dictionary.

Signal embedding

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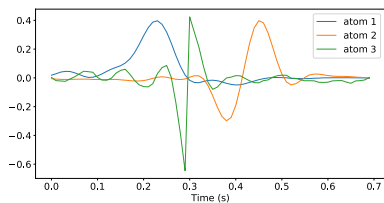
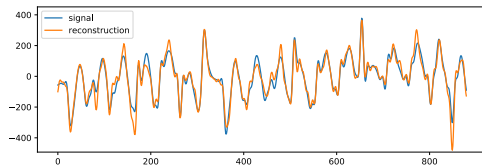
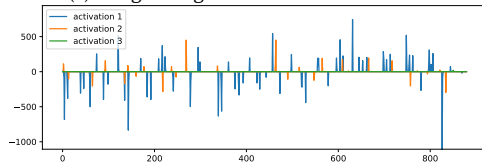


Figure: Dictionary.



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

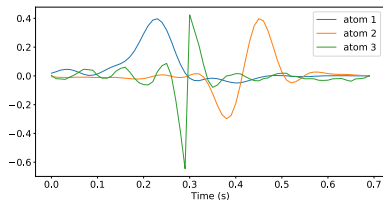
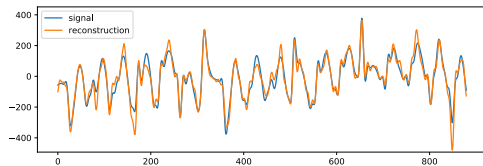
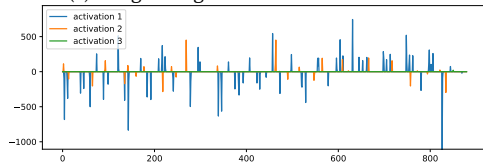


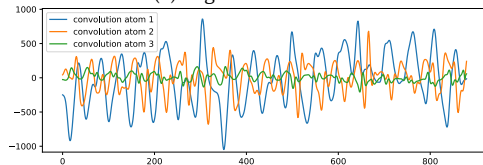
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(a) Original signal and its reconstruction



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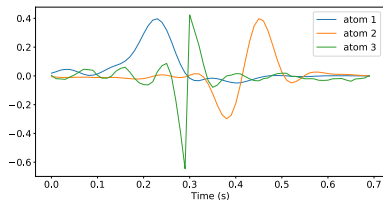
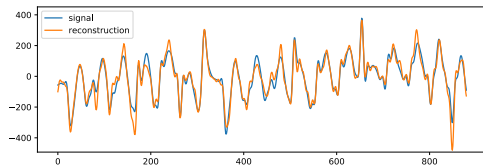
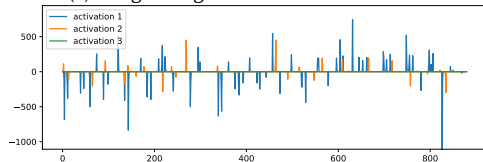


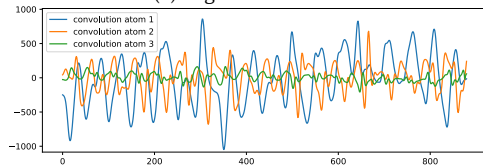
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(b) Signal activations



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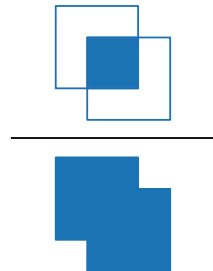
4. Conclusion

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:

$$\text{IoU}(\hat{b}) \doteq \max_j \frac{|\mathbf{b}_j \cap \hat{b}|}{|\mathbf{b}_j \cup \hat{b}|}$$

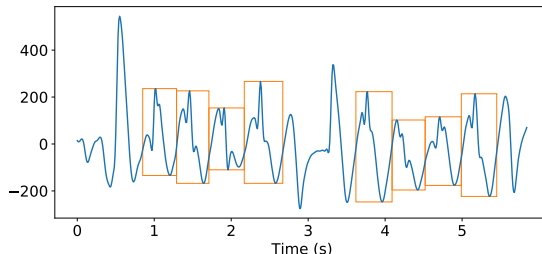
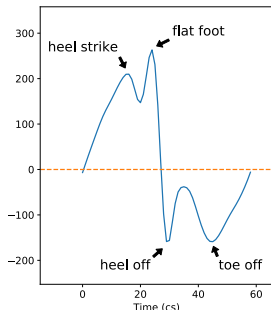
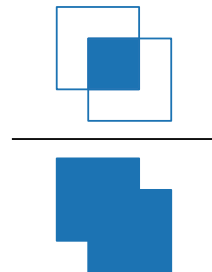


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Step proposal network

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: $\text{IoU}(b_t^k) > \sqrt{0.7}$
- ▶ Negative boxes: $\text{IoU}(b_t^k) < \sqrt{0.3}$
- ▶ Other are not used for training

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

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

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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



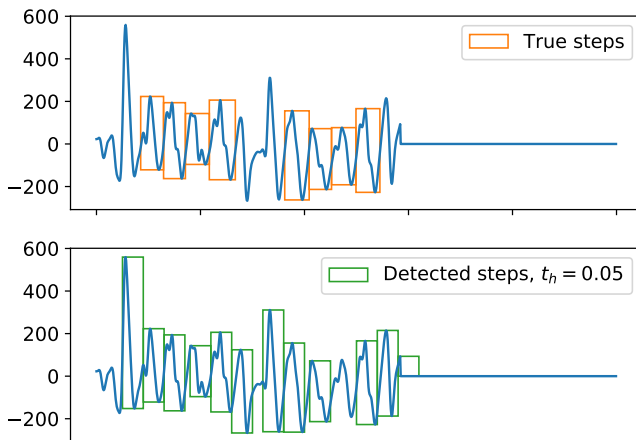
Figure: SPN training and testing errors.

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%

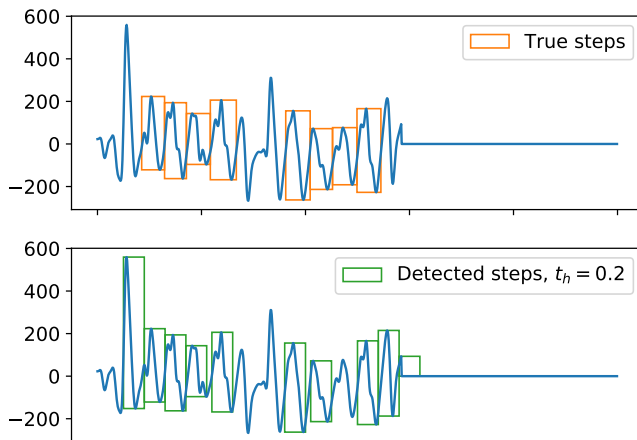
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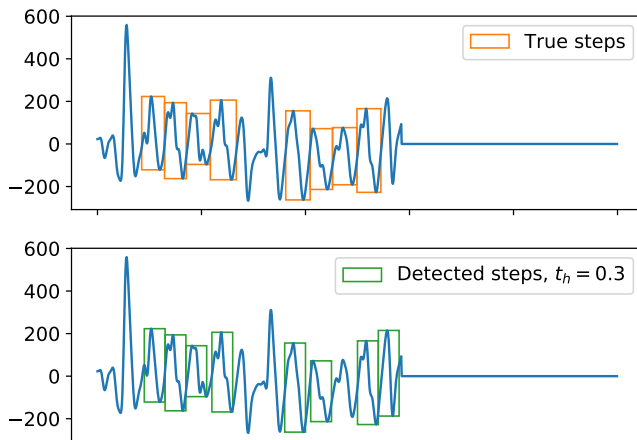
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- ▶ SPN uses the convolutional representation to detect steps
- ▶ Allows to located steps in complex signals
- ▶ Training and inference are fast

Future work

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

Conclusion

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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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