

# Scuola di Dottorato in Ingegneria dell'Informazione

## XVII Ciclo n.s., 3° anno di corso (2017/2018)



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**Progetto Eureka**



# **Ambient Intelligence: Computational Audio Processing For Human Fall Detection**

# Outline

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- **Introduction**
  - Fall Detection System and Challange
  - Motivations and Contributions
- **Dataset**
  - FAS
  - A3FALL Dataset
- **Supervised Approaches**
- **Unsupervised Approach**
  - OCSVM
  - End-To-End CNN-AE
- **Weakly-supervised Approach**
  - OCSVM + Template Matching
  - User-Aided
  - Few-shot Siamese Neural Networks
  - OneShot Siamese Autoencoders
- **Other Contributions**
- **Conclusions**
- **References**

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  - Fall Detection System and Challange
  - Motivations and Contributions
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  - FAS
  - A3FALL Dataset
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- **Unsupervised Approach**
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# Human fall: a real problem for society

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"And why do we fall, Bruce? So we can learn to pick ourselves up" cit. Alfred - Batman Begins

- 62% of injury-related hospitalizations for the people over 65 years are the result of a fall [1]
- main cause of death due to accidents for people over 65 [2]
- can lead to psychophysical repercussions on people [3]

## What can be done with FCS

- Monitoring of the elderly or people who live alone
- Assistance time reduction

# Fall Classification System Challenge [4]

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- Try to collect sufficient human fall data: supervised or analytical methods
  - difficulty in retrieving examples that represent human falls
- Deal with no human fall data: Novelty detection approach
  - good description of "normality"

## Related Work

- Wearable
  - **Accelerometers**
  - Gyroscopes
- Ambient
  - **Vision System**
  - Audio microphone
  - Radar doppler

## Issues

- no standard datasets;
- no standard methodology
- difficult comparison with other methods;
- no audio dataset available
- scarcity of real human falls

- **Introduction**

Fall Detection System and  
Challenge

Motivations and Contributions

- Dataset

FAS

A3FALL Dataset

- Supervised Approaches

- Unsupervised Approach

OCSVM

End-To-End CNN-AE

- Weakly-supervised Approach

OCSVM + Template Matching  
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Few-shot Siamese Neural  
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# Motivations and Contributions

## Analytical methods:

- exploiting some a priori knowledge;
- manual tuning of the hyperparameters;
- applying a threshold on acquired signals or features;

They can hardly perform when the operating conditions and the subjects are variable.

## Machine learning methods:

- learns from the data;
- can be forced by exploiting some a priori knowledge;
- no need of manual tuning of the hyperparameters;

They need more data!

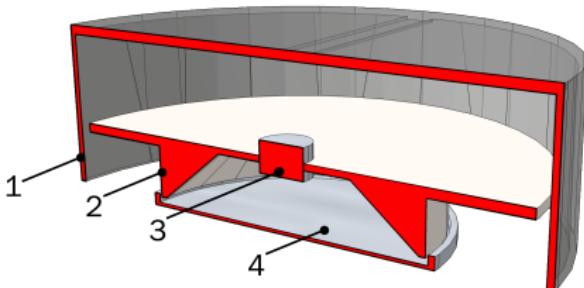
## Contributions

- audio based fall detection is a reliable alternative;
- proposal and evaluation of the FD task dedicated FAS sensor;
- proposal of the acoustic A3FALL dataset to the community.

- Introduction
  - Fall Detection System and Challange
  - Motivations and Contributions
- Dataset
  - FAS
    - A3FALL Dataset
- Supervised Approaches
- Unsupervised Approach
  - OCSVM
  - End-To-End CNN-AE
- Weakly-supervised Approach
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# Floor Acoustic Sensor[1]

1. The outer container
2. The inner container
3. The microphone slot
4. The membrane touching the floor



## Advantage

- Easily integrated into the environment
- More sensitive to signals related to falls

3D printed prototype



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  - A3FALL Dataset
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  - OCSVM
  - End-To-End CNN-AE
- Weakly-supervised Approach
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# The fall events dataset: A3Fall

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## Recording Rooms

- R0 - rectangular room particularly suitable for the propagation of acoustic waves through the floor;
- R1 - university auditorium room in which the flooring is composed of fitted carpet;
- R2 - a recording studio
  - sensors placed in the live room;
  - audio events performed in the control room.

# Recording set-up

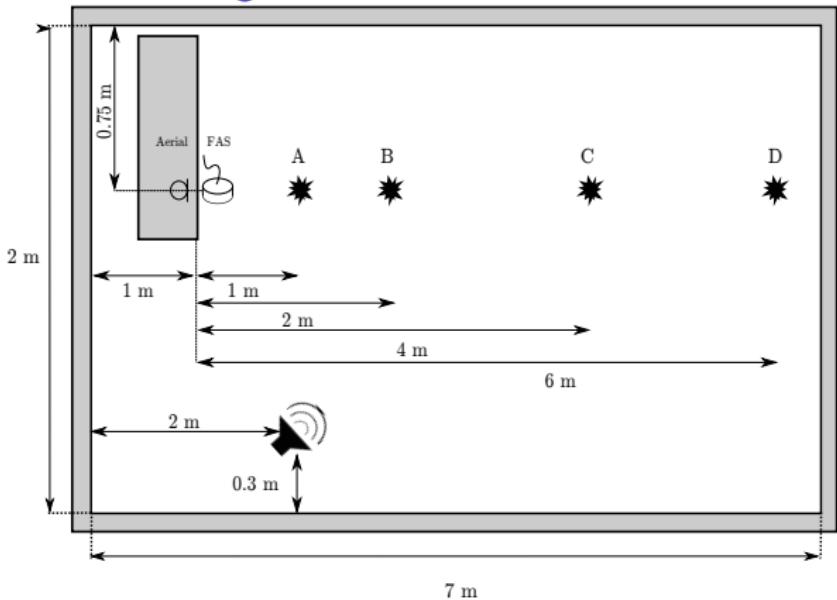
## Sampling

- Sample Rate:  
44.1 kHz
- Bit-depth:  
24 bit

Used sensors:

- Mic. array (3)<sup>1</sup>
- FAS v1<sup>1</sup>
- FAS v2<sup>1</sup>

## The recording room



<sup>1</sup>AKG C400 BLT.

<sup>2</sup>RODE Lavalier.

# Description

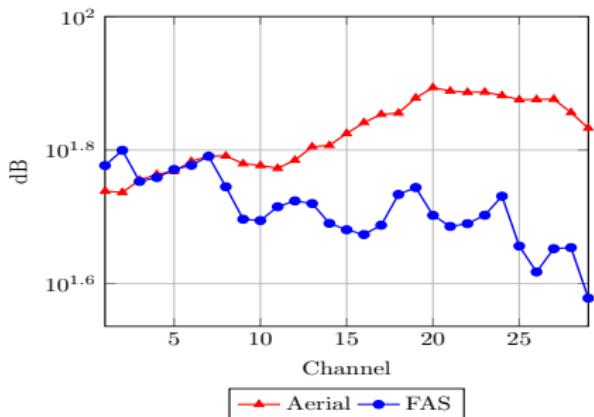
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Class	R0	R1	R2
Nr. of occurrences			
Basket	64	40	40
Fork	64	40	40
Ball	64	40	40
Book	64	40	40
Bag	64	30	40
Chair	96	40	40
Table	0	40	40
Guitar Slide	0	40	40
Nipper	0	40	40
Keys	0	40	40
Hook	0	40	40
Coat Hook	0	40	40
Manikin Doll	44	0	0
Human Fall	0	40	40
Total length (s)			
Background	2530	9055	5550

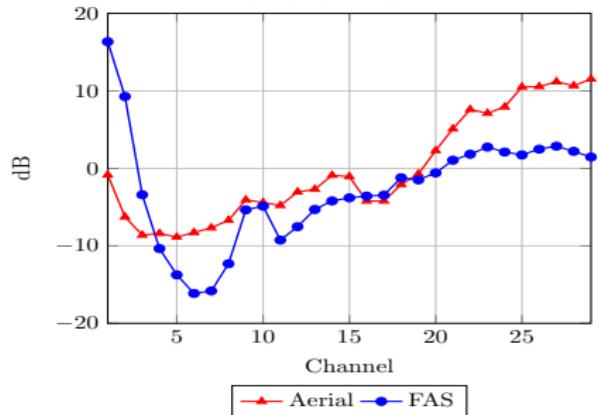


# Signals analysis

Average value of the mel channels



Average value of the SNR for each mel channel

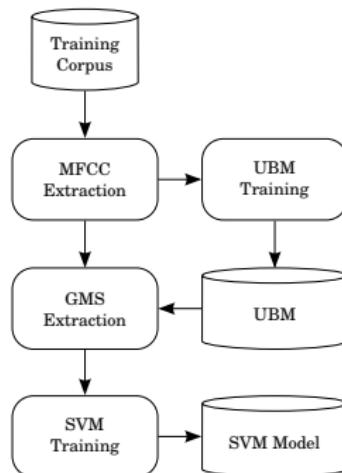
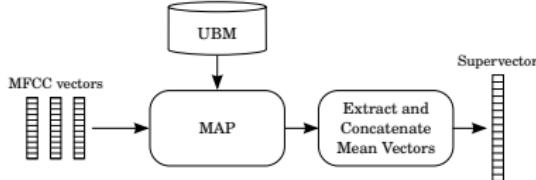


## Remark

- The “valley” in the curves is due to the pitch of the music signal
- The FAS is better at low frequencies

# Supervised Approaches: SVM based

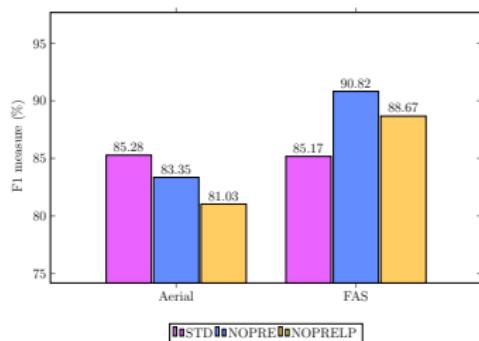
- Completely supervised scenario
- GMM to model a UBM with EM algorithm
- MFCC features to Supervectors (MAP)
- SVM classifier



# Scenarios

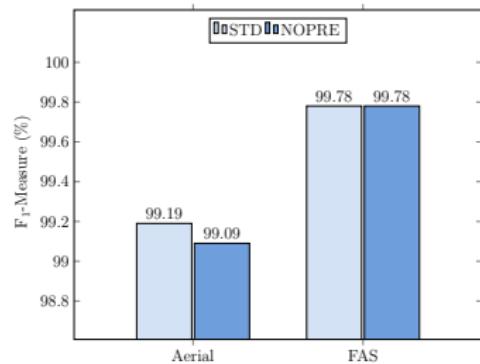
## Multi-class

Trained to discriminate the type of the fallen object



## Bi-class

Trained to discriminate fall from non-fall

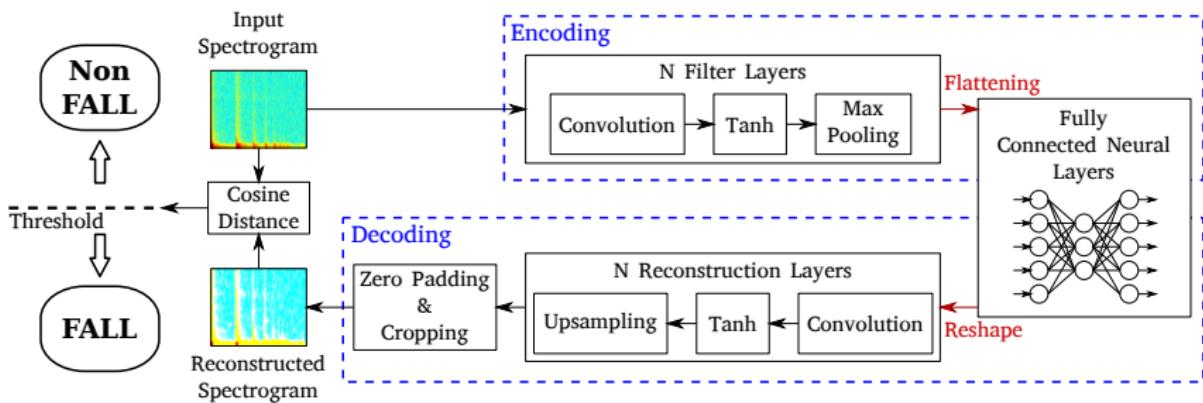


- Introduction
  - Fall Detection System and Challange
  - Motivations and Contributions
- Dataset
  - FAS
  - A3FALL Dataset
- Supervised Approaches
- **Unsupervised Approach**
  - OCSVM
  - End-To-End CNN-AE
- Weakly-supervised Approach
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- Other Contributions
- Conclusions
- References



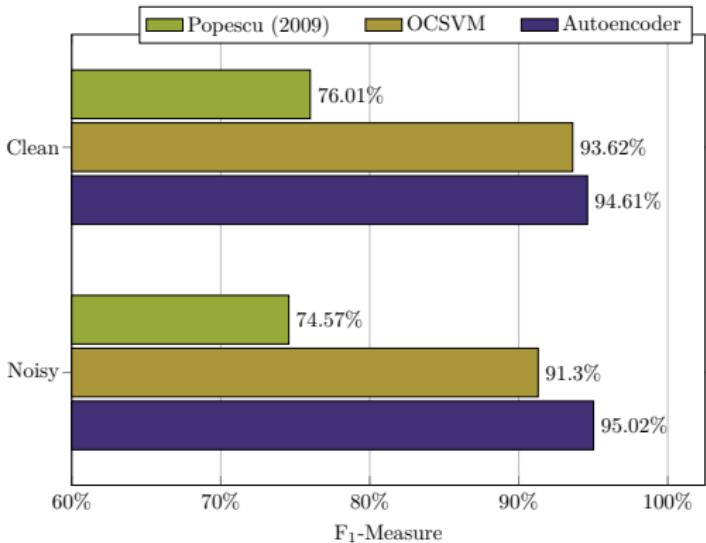
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  - Fall Detection System and Challange
  - Motivations and Contributions
- Dataset
  - FAS
  - A3FALL Dataset
- Supervised Approaches
- **Unsupervised Approach**
  - OCSVM
  - End-To-End CNN-AE
- Weakly-supervised Approach
  - OCSVM + Template Matching
  - User-Aided
  - Few-shot Siamese Neural Networks
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- References

# Unsupervised Approach



# Results

- Trained with background sounds only
- Tested with:
  - background
  - human fall

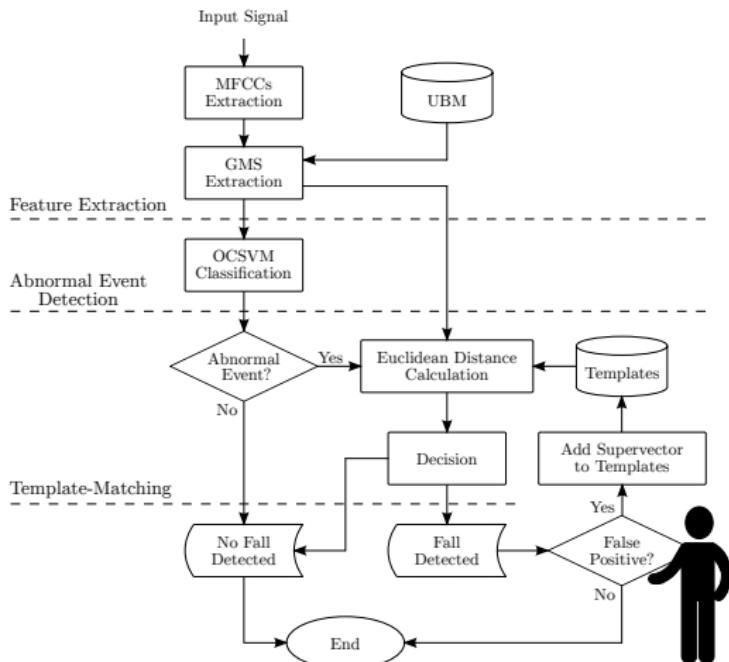




- Introduction
  - Fall Detection System and Challange
  - Motivations and Contributions
- Dataset
  - FAS
  - A3FALL Dataset
- Supervised Approaches
- Unsupervised Approach
  - OCSVM
  - End-To-End CNN-AE
- Weakly-supervised Approach
  - OCSVM + Template Matching
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  - Few-shot Siamese Neural Networks
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- Conclusions
- References

# OCSVM user-aided

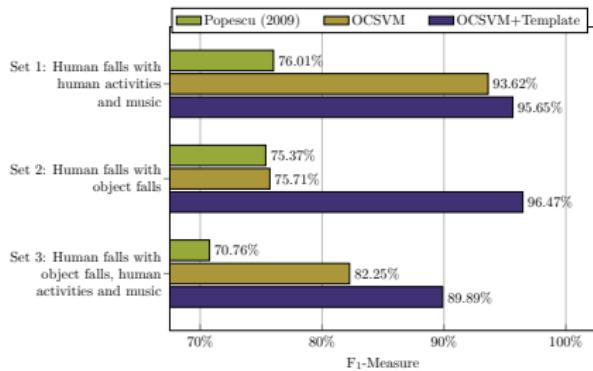
- 1° Stage: OCSVM
  - trained with non-fall event
- 2° Stage: template matching
  - based on Euclidean Distance
- Final decision
  - user-aided: false positive report



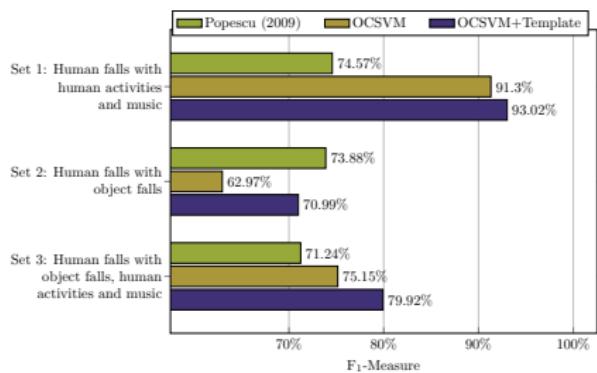
# Results



## Clean condition



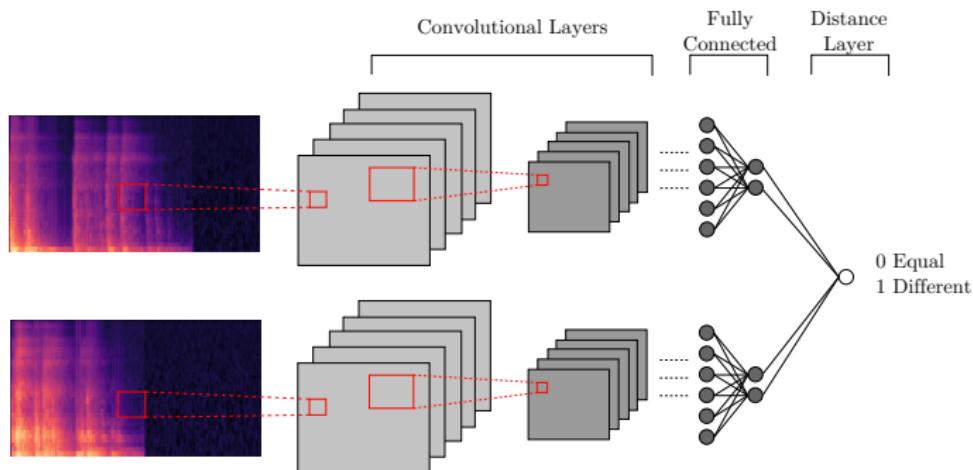
## Noisy condition





- Introduction
  - Fall Detection System and Challange
  - Motivations and Contributions
- Dataset
  - FAS
  - A3FALL Dataset
- Supervised Approaches
- Unsupervised Approach
  - OCSVM
  - End-To-End CNN-AE
- Weakly-supervised Approach
  - OCSVM + Template Matching
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# Few-shot Siamese Neural Networks



$$\text{Loss} = (1 - Y) \frac{1}{2} (E_w)^2 + (Y) \frac{1}{2} \{(\max(0, m - E_w)\}^2$$



## Training Phase

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Consider  $X_1, X_2$  as a pair of two input samples.

### Euclidean Distance

$$E_w = \|S_e(X_1) - S_e(X_2)\|. \quad (1)$$

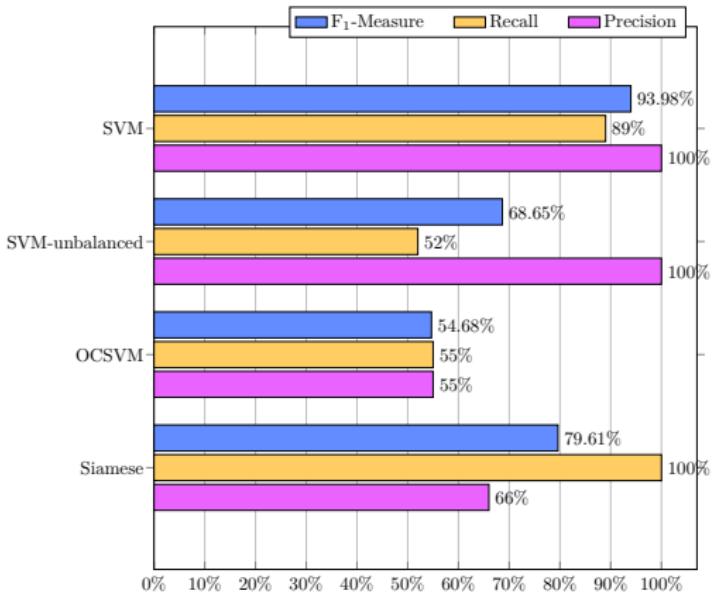
with  $S_e(X_1)$  and  $S_e(X_2)$  the mappings performed by the network

The label for training a SNN are built as follows:

- Positive examples labelled as 0: pair of input samples belonging to the same fall event class
- Negative examples labelled as 1: pair of input samples not belonging to the same fall event class

# Results

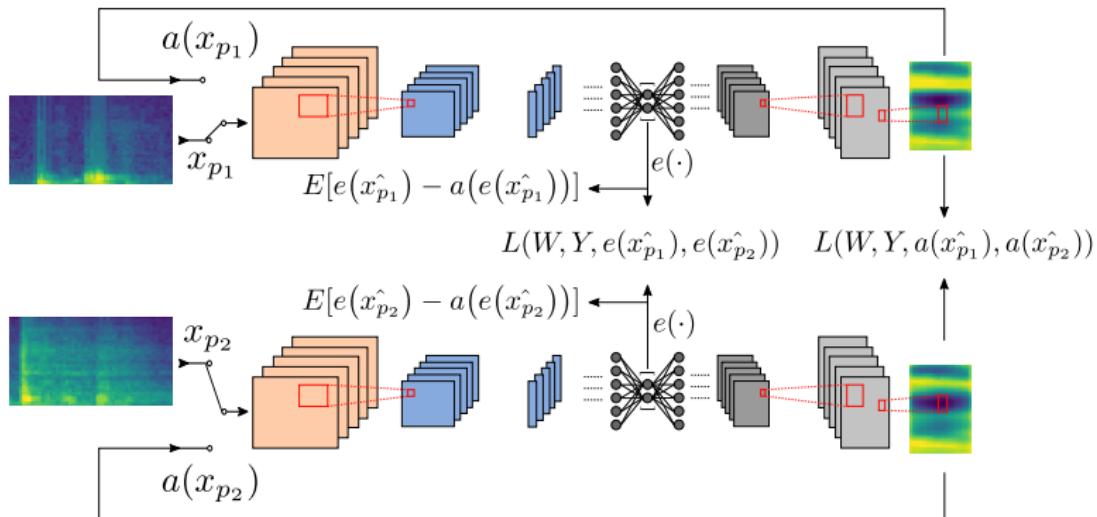
- Data augmentation
- Trained:
  - objects fall
  - 1 human fall
- Tested with:
  - objects fall
  - human fall





- Introduction
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  - OCSVM
  - End-To-End CNN-AE
- Weakly-supervised Approach
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  - OneShot Siamese Autoencoders
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- References

# OneShot Siamese Autoencoders





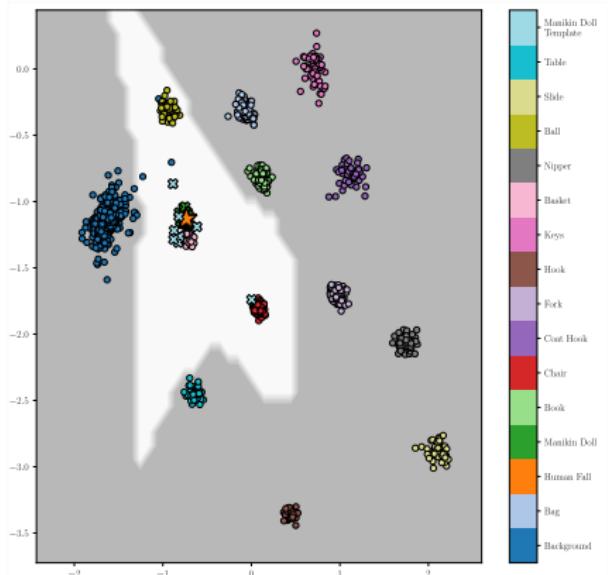
## Training procedure

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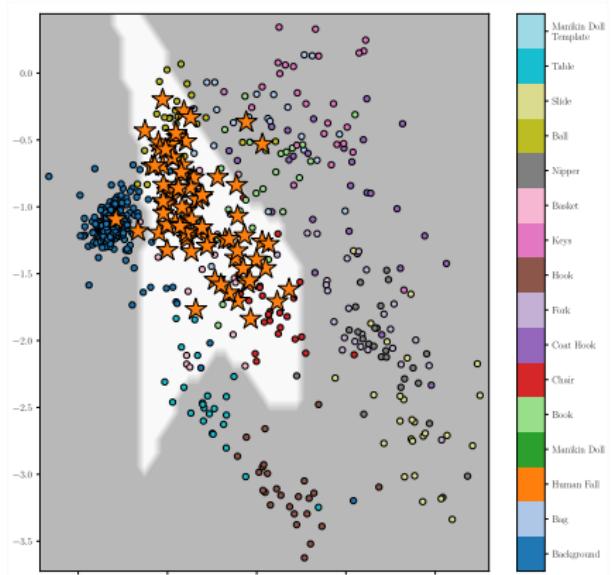
- Contrastive loss of latent spaces
- Contrastive loss of reconstructions
- Reconstruction loss (mse) of latent spaces
- To exploit the few human fall samples available a smart selection of the train pairs has been done:
  - Neither the real falls nor the simulated falls were coupled with the falls of the objects
  - Simulated and real falls were coupled together
- induces the network to make a transformation in the latent layer
- simulated human fall can be used as real human fall template in the final classifier
- KNN classifier

# Latent space with 2 neurons

Train set

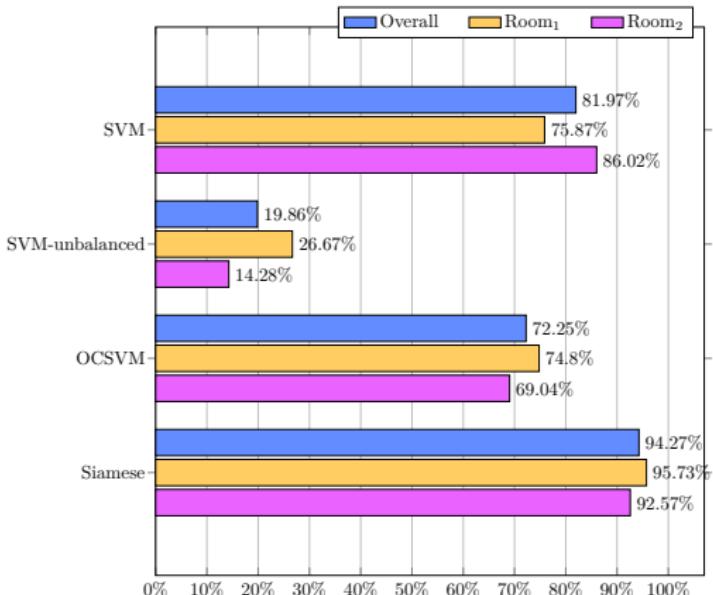


Test set



# Results

- Trained (3 room):
  - objects falls
  - backgrounds
  - manikin doll falls
  - 1 human fall per room
- Testset composed of:
  - objects fall
  - human fall
  - backgrounds



# Audio Timbre Transfer

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# Conclusions

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-  E. Principi, D. Droghini, S. Squartini, P. Olivetti, and F. Piazza,  
"Acoustic cues from the floor: a new approach for fall classification,"  
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## References (2)

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-  D. Droghini, E. Principi, S. Squartini, P. Olivetti, and P. F.,  
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-  J. Bromley, I. Guyon, Y. LeCun, E. Säckinger, and R. Shah,  
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in *Advances in Neural Information Processing Systems*, 1994, pp. 737–744.
-  G. Koch, R. Zemel, and R. Salakhutdinov,  
"Siamese neural networks for one-shot image recognition,"  
in *ICML Deep Learning Workshop*, 2015, vol. 2.



## References (3)

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D. Droghini, D. Ferretti, E. Principi, S. Squartini, and F. Piazza,  
"A combined one-class svm and template matching approach for user-aided human  
fall detection by means of floor acoustic features,"  
*Computational Intelligence and Neuroscience*, vol. 2017, 2017,  
Article ID 1512670.



# Publications List (1)

## International Journal:

[3 articles, 2 first author]

-  [1] Principi, E., Droghini, D., Squartini, S., Olivetti, P., Piazza, F.:,  
“Acoustic cues from the floor: a new approach for fall classification,”  
*Expert Systems with Applications*, 2016.
-  [2] Droghini, D., Ferretti, D., Principi, E., Squartini, S., Piazza, F.:,  
“A combined one-class svm and template matching approach for user-aided human  
fall detection by means of floor acoustic features,”  
*Computational Intelligence and Neuroscience*, 2017.

## International Journal (submitted):

[1 article, 1 first author]

-  [1] Droghini, D., Principi, E., Squartini, S., Gabrielli, L., P., Piazza.,  
“Audio Metric Learning by using Siamese Autoencoders for One-Shot Human Fall  
Detection,”  
*IEEE Transactions on Emerging Topics in Computational Intelligence*, 2018,  
submitted.

## International Conference:

[14 articles, 5 first author]



## Publications List (2)

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[1] Droghini, D., Principi, E., Squartini, S., Olivetti, P., Piazza., F.,  
"Human fall detection by using an innovative floor acoustic sensor,"  
in *Proc. of WIRN*, Vietri sul Mare, Italy, May, 2016.



[2] Gabrielli, L., Cella, E., Vesperini, F., Droghini, D., Principi, E., Squartini, S.,  
"Deep Learning for Timbre Modification and Transfer: An Evaluation Study,"  
in *Proc. of AES*, Milan, Italy, May, 2018.



[3] Droghini, F., Vesperini, F., Principi, E., Squartini, S., Piazza., F.,  
"Few-shot Siamese Neural Networks employing Audio features for Human-Fall  
Detection",  
in *Proc. of PRAI*, Kean University, Union, NJ, USA, Aug 2018.



[4] Vesperini, F., Droghini, D., Principi, E., Gabrielli, L., Squartini, S.,  
"Hierarchic ConvNets Framework for Rare Sound Event Detection",  
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### Others:



## Publications List (3)

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-  F. Vesperini, D. Droghini, D. Ferretti, E. Principi, L. Gabrielli, S. Squartini, and F. Piazza,  
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