

Feature extraction for human activity recognition on streaming data

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Outline

➤ Introduction

- Human Activity Recognition using simple binary sensors

➤ Methods

- Offline and Online Human Activity recognition
- Data segmentation
- Feature extraction

➤ Results

➤ Conclusions

Introduction

Objective: Using sensors placed on daily objects to identify high level human activities such as take medicine, sleeping, etc.



✓ Applications

- ✓ Health/Elderly care
- ✓ Emergency
- ✓ Security
- ✓ Smart Environment
- ✓ Surveillance
- ✓ Context-aware-systems

✓ Sensor types

- ✓ Contact switch sensors, pressure sensors, object identification sensors, etc.
- ✓ Camera

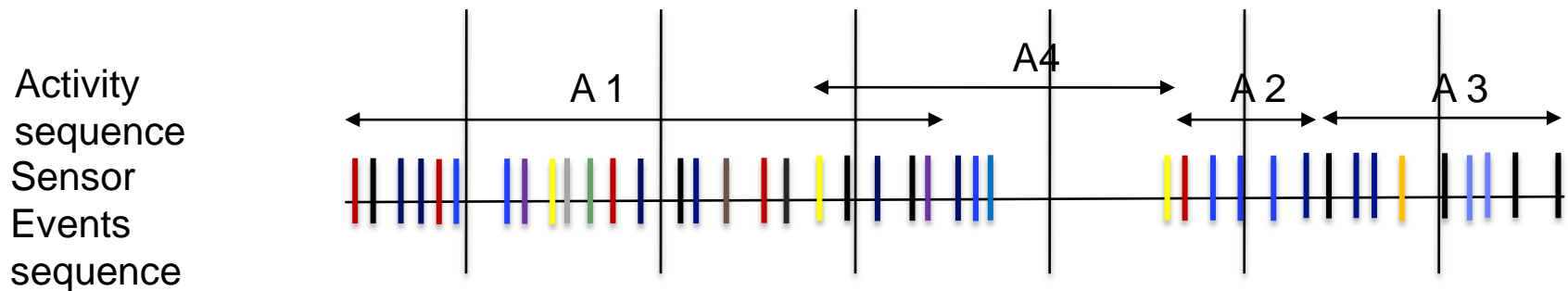
✓ **Binary sensors are simple, cheap , easy to installed, and NOT as INTRUSIVE as camera.**

Data Segmentation



✓ Segmentation

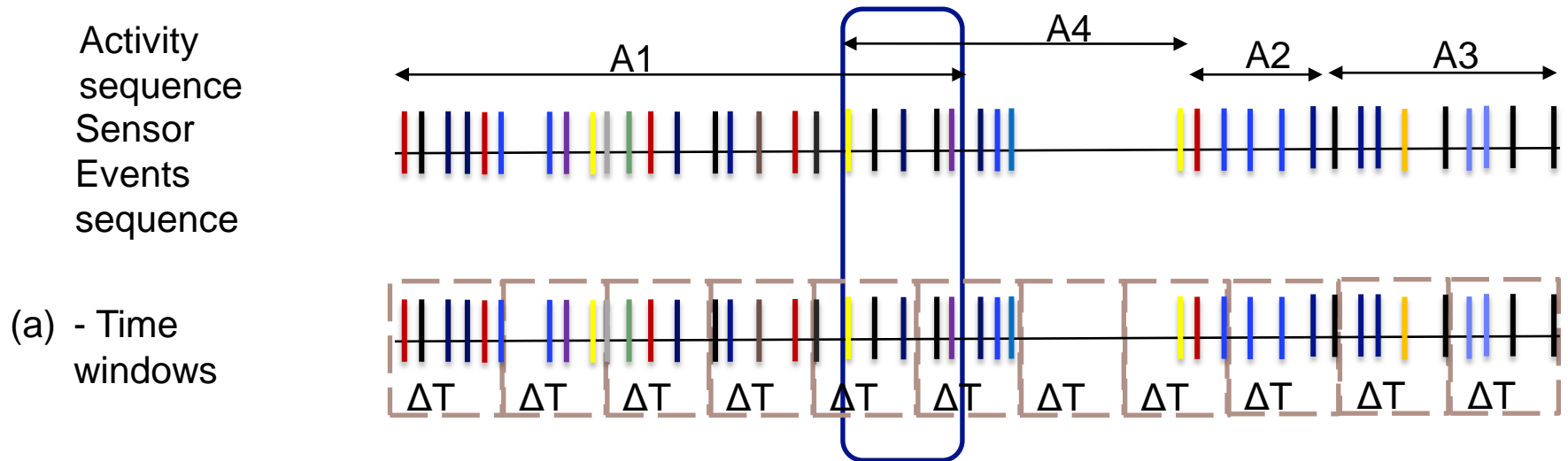
- ✓ Divide the data into windows most suitable for activity recognition
- ✓ On each window a feature vector is computed to use it as an instance for learning or testing phase.
- ✓ A difficult task:
 - ✓ Human activities can be performed consecutively or concurrently → The exact boundaries of an activity are difficult to define.



Offline vs. Online methods (1)

✓ Offline method

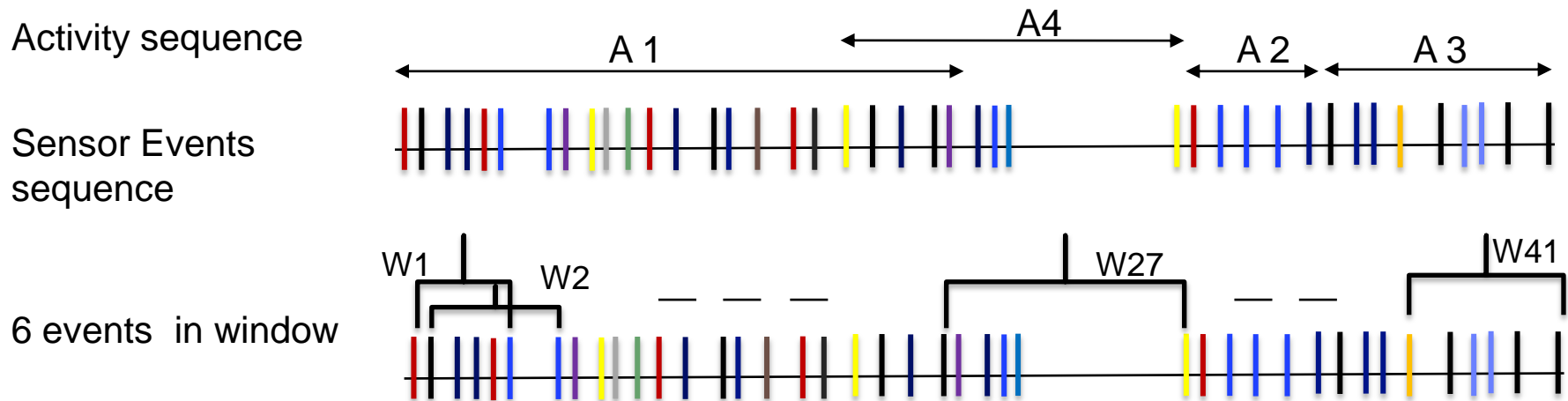
- ✓ Segment data into time slices
- ✓ Each time slice labeled with activity that dominates it.
- ✓ Wait for future data to identify which activity is being executed (duration of the window)
- ✓ Suitable for sequential activities, it is not effective in the case of interleaved or concurrent activities.



Offline vs. online methods (2)

✓ Online method

- ✓ The method classify each event when recorded.
- ✓ Data is segmented into windows of K sensor events.
- ✓ Each window contains events that precede the last one and describe it .
- ✓ Each window is labeled with the one of the last event.
- ✓ Suitable for non sequential activities and multi-residents smart-home.
- ✓ Better for health-care or assistance in living applications that require prompt intervention/reaction.

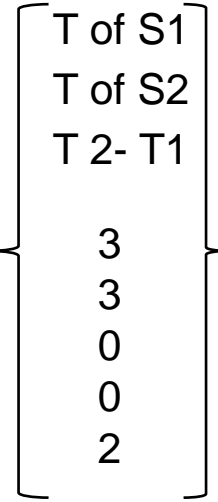
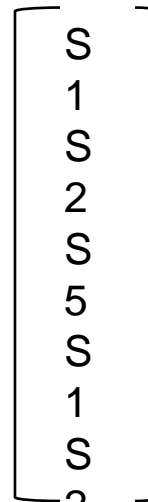


Feature extraction (1)

1. BaseLine feature extraction method (with 5 sensors in the smart-home)

Window of 9 events

Feature vector



Time of first event
Time of last event
Duration

How often **each sensor appear in the window**

Vector is labeled with the activity of the last even (**S1**)

Drawback: window can contain sensor events far away from the last one (in time)

→ perhaps do not correctly describe the last event?

Feature Extraction (2)

2. Sensor-Dependency extraction

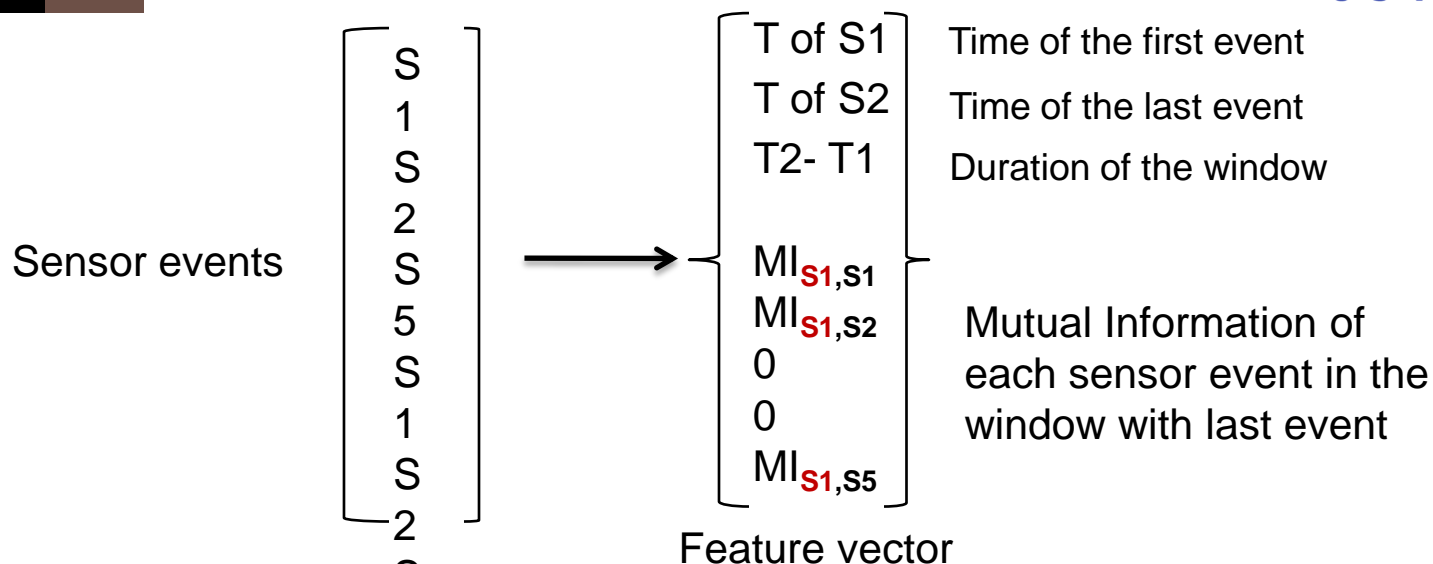
Computation of a mutual information matrix **MI** between sensors on the whole stream. For N sensors, NxN matrix (example still with 5 sensors).

$$\mathbf{MI} = \begin{bmatrix}
 MI_{s1,s1} & MI_{s2,s1} & MI_{s3,s1} & MI_{s4,s1} & MI_{s5,s1} \\
 MI_{s2,s1} & MI_{s2,s2} & MI_{s3,s2} & MI_{s4,s2} & MI_{s5,s2} \\
 MI_{s3,s1} & MI_{s2,s3} & MI_{s3,s3} & MI_{s4,s3} & MI_{s5,s3} \\
 MI_{s4,s1} & MI_{s2,s4} & MI_{s3,s4} & MI_{s4,s4} & MI_{s5,s4} \\
 MI_{s5,s1} & MI_{s2,s5} & MI_{s3,s5} & MI_{s4,s5} & MI_{s5,s5}
 \end{bmatrix}$$

MI_{s_i,s_j} represents the probability of appearance of s_i just before s_j

Higher $MI_{s1,s2}$ is, stronger is the relationship between s_1 and $s_2 \Rightarrow$ a strong influence between them for an activity.

Feature extraction (3)



3. Sensor Dependency feature extraction EXTENDED method

- ✓ In the previous method, Mutual information is computed on the consecutive apparition of two sensor events.
- ✓ In this extension, computation is done in a window of K sensors instead

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→ with this modification allow more than one path of execution for each activity.

Feature extraction (4)

4. Last State Sensor feature extraction method

Window of
sensor
events

Event value

Feature vector

S
1
S
2
S
5
S
1
S
2
S

ON
ON
OFF
OFF
OFF
OFF
ON
ON
OFF

T of S1
T of S2
T 2- T1

0
0
0
0
1

Time of the first event
Time of the last event
Duration of the window

Last value of each
sensor in the window

- ✓ It is efficient for instance with IR sensors of different kind (large and small cone).
- ✓ The last value of the sensor in the windows became more descriptive for the last event.

➤ Datasets from WSU CASAS smart-home project

Dataset	Gender & age	Number of Sensors	Time Interval
Aruba	Elderly / female	34	7 months
Tulum	2 married residents	16	4 months

➤ Classification stage

One vs. one SVM (LibSVM library)

➤ Experiment:

Two series of experiments:

- ✓ Learning on data excluding the “other” activity
- ✓ Learning on data containing “other” activity

(« Other » activity: data with missing labels, transitions, etc.)

Results

Learning excluding 'other events'				
Feature extraction Method	Aruba dataset		Tulum dataset	
	Acc	F-score	Acc	F-score
Baseline	87.23	63.29	63.46	35.60
Sensor Dependency	87.71	65.56	64.18	39.30
Sensor Dependency extension	87.71	68.68	65.57	41.29
Last Stat Sensor	87.55	69.24	63.95	36.91

Learning data containing 'other events'				
Feature extraction Method	Aruba dataset		Tulum dataset	
	Acc	F-score	Acc	F-score
Baseline	67.82	49.52	63.32	35.75
Sensor Dependency	64.18	47.54	63.48	36.71
Sensor Dependency extension	67.38	50.39	65.26	39.01
Last Stat Sensor	69.09	47.38	63.90	34.81

Conclusions & future works

- ✓ We achieved a classification rate of over 69% on data containing “Other” activity.
- ✓ Last Stat Sensor feature extraction method gives the best performance in that case.
- ✓ Performance of recognition system is sensitive to the problem of missing labels data.
- ✓ **Improving the performance of the system using data containing “other” activity .**
- ✓ **Finding a way to improve the computational complexity.**

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