Introducing Knowledge in the Process of Supervised Classification of Activities of Daily Living in Health Smart Homes

A. Fleury², N. Noury^{1,3} and M. Vacher⁴

¹TIMC-IMAG Lab, Team AFIRM, UMR CNRS/UJF 5525, Grenoble ²École des Mines de Douai, Computer Sciences and Control Dpt., Douai, France ³INL Lab, Team MMB, UMR CNRS/ECL/INSA/UCBL 5270, Lyon, France ⁴LIG Lab, Team GETALP, UMR UJF/CNRS/INPG 5217, Grenoble, France



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Outline of the presentation

- Introduction and Objectives
- 2 Data Acquisition
- Classification of ADLs
- Prior Knowledge Introduction
- **5** Conclusion and Discussion

Context of the study Related Works Objectives of the Work

Context of the study

Facts

- Ageing population is growing faster than institution equipped to welcome them in developed countries.
- ► In France, population over 85 is nowadays 1.3 million and previsions for 2015 are more than 2 millions.
- ► Same previsions in the whole world ⇒ Loss of autonomy is an important problem to care about.

Possible solution ?

Smart sensors and smart homes to:

- Monitor the persons at home and detect distress situations
- Evaluate and observe his/her activity continuously (to detect early symptoms or monitor autonomy)

Context of the study Related Works Objectives of the Work

Related Works

Several works for automatic classification of activities in different environments:

- Philipose et al., 2004 ⇒ RFID tags on hundreds of objects, 14 activities, Dynamic Bayesian Networks
- Hong et al., 2008 ⇒ RFID tags on foods etc., Hygiene vs. preparing a drink, Dempster-Shafer. Nugent et al. tested also the impact of sensor failure.
- Kröse et al., 2008 ⇒ Lots of sensors (environmental, switches...), Going to the toilets vs exit from the flat, HMM.
- Berenguer et al., 2009 ⇒ Sensor: electrical powerline, activity of taking a meal.

Context of the study Related Works **Objectives of the Work**

Objectives of the Work

Objectives of the project

- AILISA and HIS projects (Health Smart Home) of the TIMC-IMAG Laboratory, faculty of Medicine of Grenoble.
- Objectives:
 - Find the optimal set-up of sensors for analyzing the activities of daily living at home,
 - Identifying the higher number of activities of daily living,
 - Linking it to autonomy-related scales used by geriatricians.

Objectives of this work

- Improving the results of the classification of ADLs obtained with SVM
- For this, testing different priors to improve the classification

Health Smart Home of Grenoble Experimental protocol Data Processing and Indexing

Health Smart Home - TIMC-IMAG Lab, Grenoble



Description & equipment of the smart home of TIMC-IMAG.

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Experimental Protocol

Population and experimentation

- Data on 13 young and healthy subjects (6 women et 7 men)
- Mean age: 30.4 yo (24 43 yo, min-max)
- Mean execution time: 51min 40s (23min 11s 1h 35min 44s, min-max)
- Seven activities, to perform at least once by every person
- 3 minutes time frames, with following repartitions:

Class	Name	Repartition	
Sleeping	C1	49	21.1%
Resting	C2	73	31.5%
Dressing/undressing	C3	16	6.9%
Having meal	C4	45	19.4%
Elimination	C5	16	6.9%
Hygiene	C6	14	6.0%
Communication	C7	19	8.2%
Total		252	100%

Data Processing

Modality	Features
Actimeter	Percentage of time spent in various postures and walking
Microphones	Number of events per kind of sounds and for each microphone
IPR	Percentage of time in each room, number of events for each PIR
Door contacts	Percentage of time "open" and predominant posi- tion (open or close)
Environmental	Differential measure for the last 15 minutes for both temperature and hygrometry

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Time-stamping

Manual indexation using video recordings:











SVM for ADLs Classification First Results

Multimodality for ADLs Classification



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Knowledge for supervised classification of ADL

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SVM for ADLs Classification First Results

SVM for ADLs Classification

- SVM (Boser et Vapnik, 1992): Binary classification (linear or non-linear using kernel and feature space)
- Method multiclass classification: one-against-one



- $\frac{N \cdot (N-1)}{2}$ SVM (for N classes)
- Differentiate the classes C_i and C_j , $0 < i \le N$ et 0 < j < i
- Majority voting:

 $C = \max_{k=1..N} \operatorname{Card}\left(\{y_{i,j}\} \cap \{k\}\right)$

SVM for ADLs Classification First Results

First Results

Global Error Rate: 13.79%.

	Classification Results							
	C1	C2	C3	C4	C5	C6	C7	
	Sleeping	Resting	Dressing	Eating	Elimination	Hygiene	Communication	
C1	98%	2%	0%	0%	0%	0%	0%	
, C2	16.4%	78.1%	0%	1.4%	4.1%	0%	0%	
ES E	13.3%	6.7%	80%	0%	0%	0%	0%	
. <u>5</u> C4	0%	0%	2.2%	97.8%	0%	0%	0%	
τ ⁵ C5	0%	6.2%	0%	6.3%	81.2%	6.3%	0%	
C6	7.1%	0%	0%	7.1%	14.3%	71.5%	0%	
C7	5%	10%	5%	0%	0%	0%	80%	

Table: Confusion Matrix for the leave-one-out validation protocol with Generic Models.

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Temporal Knowledge Spatial Knowledge Hybridization of Spatial and Temporal Knowledge

Introducing Temporal Knowledge

Time slots

Seven time slots:

- T1: breakfast (7–9 AM)
- T2: morning (9–12 AM)
- T3: lunch (12 AM-2 PM)
- T4: afternoon (2–7 PM)
- T5: diner (7 PM-9 PM)
- T6: evening (9-11 PM)
- T7: night (11 PM-7 AM)

Slots of activities

Each activity is affected to a restricted number of time slots:

Class	Τ1	Т2	Т3	Τ4	Т5	Т6	Τ7
Sleeping	\checkmark			\checkmark	\checkmark	\checkmark	
Resting	\checkmark	\checkmark		\checkmark	\checkmark	\checkmark	
Dress/undress	\checkmark	\checkmark				\checkmark	\checkmark
Having meal	\checkmark		\checkmark		\checkmark		
Elimination	\checkmark						
Hygiene	\checkmark	\checkmark	\checkmark		\checkmark		
Communication	\checkmark						

Interest of this introduction

Reducing the possibilities for the frame considering the slot

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Temporal Knowledge Spatial Knowledge Hybridization of Spatial and Temporal Knowledge

Results of Introduction of Temporal Knowledge

Global Error Rate: 9.91%.

	Classification Results							
	C1	C2	C3	C4	C5	C6	C7	
	Sleeping	Resting	Dressing	Eating	Elimination	Hygiene	Communication	
C1	100%	0%	0%	0%	0%	0%	0%	
, C2	11%	83.6%	0%	0%	2.7%	1.3%	1.4%	
.≝ C3	0%	13.3%	86.7%	0%	0%	0%	0%	
.≣ C4	0%	0%	2.2%	97.8%	0%	0%	0%	
τ ο C5	0%	12.5%	0%	0%	87.5%	0%	0%	
C6	0%	0%	0%	7.1%	14.3%	78.6%	0%	
C7	0%	5%	5%	5%	0%	0%	85%	

Table: Confusion Matrix for the leave-one-out validation protocol with temporal knowledge.

Temporal Knowledge Spatial Knowledge Hybridization of Spatial and Temporal Knowledge

Introducing Spatial Knowledge



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Knowledge for supervised classification of ADL

Temporal Knowledge Spatial Knowledge Hybridization of Spatial and Temporal Knowledge

Results of Introduction of spatial Knowledge

Global Error Rate: 21.12%.

	Classification Results							
	C1	C2	C3	C4	C5	C6	C7	
	Sleeping	Resting	Dressing	Eating	Elimination	Hygiene	Communication	
C1	69.4%	2%	0%	28.6%	0%	0%	0%	
, C2	11%	78%	0%	6.9%	4.1%	0%	0%	
.≝ C3	13.3%	6.7%	73.3%	6.7%	0%	0%	0%	
.≣ C4	0%	0%	2.2%	97.8%	0%	0%	0%	
τ υ C5	0%	0%	0%	6.2%	87.5%	6.3%	0%	
C6	0%	0%	0%	14.3%	14.3%	71.4%	0%	
C7	5%	10%	10%	10%	0%	0%	65%	

Table: Confusion Matrix for the leave-one-out validation protocol with spatial knowledge.

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Temporal Knowledge Spatial Knowledge Hybridization of Spatial and Temporal Knowledge

Introducing Hybridized (Spatial/Temporal) Knowledge

Construction

- First consider the decision taken by the classification using Temporal Knowledge
- Then consider the decision taken with Spatial Knowledge.

Two cases then:

- Decisions are coherent: this decision is kept as the result
- Decisions are not: Generic estimation is performed.

Temporal Knowledge Spatial Knowledge Hybridization of Spatial and Temporal Knowledge

Results of Introduction of Hybridized Knowledge

Global Error Rate: 13.2%.

	Classification Results							
	C1	C2	C3	C4	C5	C6	C7	
	Sleeping	Resting	Dressing	Eating	Elimination	Hygiene	Communication	
C1	98%	2%	0%	0%	0%	0%	0%	
, C2	16.4%	78.1%	0%	1.4%	4.1%	0%	0%	
EO E	13.3%	6.7%	80%	0%	0%	0%	0%	
.≣ C4	0%	0%	2.2%	97.8%	0%	0%	0%	
τ υ C5	0%	0%	0%	6.2%	87.5%	6.3%	0%	
C6	7.1%	0%	0%	7.1%	14.3%	71.5%	0%	
C7	5%	10%	5%	0%	0%	0%	80%	

Table: Confusion Matrix for the leave-one-out validation protocol with hybridized knowledge.

Discussion and Conclusion

Conclusion

- Time of the day is the best indicator in this case \Longrightarrow Effect of Perfection of the sensor
- Spatial knowledge have lower results ⇒ lots of mis-detection for the PIR sensors
- ullet \Longrightarrow Hybridization does not significantly improve the results

Discussion

- Generic models: more complicated but best results with imperfect sensors
- Knowledge do not improve significantly the results but degrade the generality of the models
- As a consequence, generic models should represent the best solution
- More experimentations and improvement of the quality of the sensors should confirm these results

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Thank you for your attention. Questions ?



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