

### Towards the Combination of Statistical and Symbolic Techniques for Activity Recognition

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#### Outline

- Introduction
- Statistical techniques
- Symbolic techniques
- Towards a hybrid framework
- Conclusions

#### Introduction

• Human activity recognition is about detecting:

- Actions / gestures
- Physical /ADL activities
- Interactions
- Based on:
  - Sensor data
  - Object use
  - Location

## Applications

- Pervasive computing
- Health-care
- Recognition of critical events
- Training
- Homeland security















#### Activity-awareness











Modeling/reasoning







Adaptation /decision making







#### Issues

- Accurate recognition of complex activities and interactions
- Dynamic sensor configurations
- Scalability
- Obtrusiveness
- Privacy



The most profound technologies are those that disappear

## Statistical techniques

- Use of sound, image and scene recognition software
  - N. Oliver *et al.*: Layered Representations for Human Activity Recognition. In: Proc. of ICMI-02
  - O. Brdiczka *et al.*: Learning Situation Models for Providing Context-Aware Services. In: Proc. of HCI 2007
  - ...
- Pros:
  - Effective for smart home/office applications
- Cons:
  - Limited to confined environments
  - Subject to privacy concerns







### Statistical techniques

- Based on body-worn sensors and on machine learning techniques
- From multiple locations to multi-modal activity recognition:
  - e.g., T. Choudhury *et al*.: The Mobile Sensing Platform: An Embedded

Activity Recognition System. In: IEEE Perv. Comp. 7(2), 2008

- Pros:
  - Non-obtrusive, embeddable in portable devices
- Cons:
  - Restricted to a limited number of activities

The alarm clock, alerted by Sal's restless rolling before waking, ...

### Statistical techniques

- Surrounding environment, objects' use, and accelerometer data
  - S. Wang *et al*.: Common Sense Based Joint Training of Human Activity Recognizers. In: Proc. of IJCAI-07.



- M. Stikic *et al.*: ADL Recognition Based on the Combination of RFID and Accelerometer Sensing. In: Proc. of Pervasive Health 2008
- Pros: very effective for recognizing ADL
- Cons: it is unlikely that in a near future all of the objects in our environment will be tagged

- Symbolic techniques are well-suited for recognizing complex activities
  - Expressing constraints and relationships among context data
- A language is needed to formally define activities
- Need to handle uncertainty
- Several different conditions can be stated to determine the same activity
- Recognition relies on simpler observations
  - giving a class := the actor is a teacher, the actor's current location is a classroom, some students are in the classroom, and the actor is writing on a blackboard

Meetings consist of

several people

spending time in

the same room

S.W. Loke: Six

ways to tell if you

are in a meeting,

CoMoRea'o6

- Various symbolic formalisms have been investigated to handle activities (and context)
- Description logics (DL) have emerged because:
  - They provide complete reasoning
  - They are supported by optimized reasoning tools
- DL allow *ontologies* to be defined
  - A domain is modeled by classes, individuals, and complex relationships among them
  - The language of choice is generally OWL-DL

• Expressivity: OWL-DL lacks important operators

• Property composition:

 $\texttt{isColleagueOf} \equiv \texttt{isEmployedBy} \circ \texttt{isEmployerOf}$ 

#### • Role-value maps:

Person  $\sqcap$  (hasCurrentLocation = hasWorkLocation)

- OWL-2 promises to overcome some limitations of OWL-DL while retaining decidability
  - B. Motik *et al.* : OWL 2 Web Ontology Language: Structural Specification and Functional-Style Syntax. W3C Working Draft. 02 December 2008

- OWL-DL coupled with rule-based reasoning
  - H. Chen *et al.*: Semantic Web in the Context Broker Architecture. Proc. of PerCom 2004
  - X.H. Wang *et al*.: Ontology based context modeling and reasoning using OWL. CoMoRea'04
  - A. Agostini *et al.*: Loosely Coupling Ontological Reasoning with an Efficient Middleware for Context-awareness. Proc. of MobiQuitous 2005
- Fact-based models
  - J. Indulska *et al.*: Towards a Standards-Based Autonomic Context Management System. Proc. of PerCom 2008

How can we

recognize

"spontaneous

urgent meetings"?

#### **OWL-based techniques**

- Even without expressive constructors, reasoning with OWL-DL is expensive
  - Ontological reasoning should be performed offline on powerful machines
  - Some optimizations can help:
    - A. Agostini *et al.:* A performance evaluation of ontology-based context reasoning. CoMoRea'07.



#### Drawbacks of existing techniques

- Statistical:
  - Recognition of complex activities
  - Static assumptions about sensors configurations
  - Scalability
  - (in some cases) Practicality and privacy issues
- Symbolic:
  - Cannot recognize basic physical activities and observations
  - (in some cases) Expressiveness and efficiency issues; do not handle uncertainty and fuzzyness

### Towards a hybrid framework

- Overall goal: coupling symbolic and statistical methods to get the best of the two worlds
- Research issues:
  - Devising a hybrid intelligent system
  - Defining a common ontology for activities and context data
  - Efficiency
  - Flexibility
  - Enforcing *privacy*

#### Towards a hybrid framework

#### Overall framework



# Towards a hybrid framework: symbolic technique

- Language requirements:
  - Sufficient expressiveness
  - Decidability
  - Support for uncertainty and/or fuzzyness
  - Interoperability with OWL
- A candidate: *fuzzyDL* 
  - Developed at ISTI-CNR
  - Includes expressive contructors
  - An optimized reasoner is actively maintained
  - Compatible with OWL-Lite

#### Towards a hybrid framework: statistical technique

- Requirements:
  - Good recognition performance
  - Run-time efficiency
  - Modularity
- Candidate technique: modular neural networks



#### Towards a hybrid framework: hybrid intelligent system

- Modular hybrid system
  - Composed of separate neural and symbolic units
  - Binding provided by the common ontology
    - each neural output node corresponds to an activity concept
  - Results combined by a *response integrator*



# Towards a hybrid framework: response integration

- Reasoning units:
  - Symbolic unit: provides fuzzy results
  - Statistical units: provide uncertain results
- Integration can be based on fuzzy integrals:
  - Non-linear function defined w.r.t. fuzzy measures (e.g., the gλ-fuzzy measure of Sugeno)
  - Other techniques may be investigated



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# Preliminary implementation: symbolic technique

 Traditional (non-fuzzy) ontology: OWL-DL





Class	Descendants
Activity	35
Artifact	43
CommunicationRoute	14
Person	4
SymbolicLocation	30
TimeExtent	11
	1

# Preliminary implementation: symbolic technique

- Ontological reasoning: crisp technique
- Can activity *A* be executed in context *C*?
  - Add an assertion stating that an instance of *A* is performed in an instance of *C*
  - Perform consistency checking to detect whether the execution *A* is consistent with *C*

```
BrushingTeeth ⊑ PersonalActivity □ ∀ performedIn.(∃hasArtifact.Sink) □ ...

RestRoom ⊑ Room □ ∃ hasArtifact.Sink □ ...

LivingRoom ⊑ Room □ ¬∃hasArtifact.WaterFixture □ ...

BrushingTeeth(CURR_ACT);RestRoom(CURR_LOC_1);LivingRoom(CURR_LOC_2)

performedIn(CURR_ACT,CURR_LOC_1); isABoxConsistent()
```

#### Preliminary implementation: machine learning technique

- Various techniques have been tried (NN, NB, SVM, MLR, ...)
- Temporal smoothing based on a sliding window
- Response integration is based on the matrix obtained from the symbolic reasoner:
   I 2 3 4 5 6 7 8 9 1
   Garden 0 0 0 1 1 1 1 0 0
   HospitalBuilding 1 0 0 0 1 0 1 0 1

	1	2	3	4	5	6	7	8	9	10
Garden	0	0	0	1	1	1	1	0	0	0
HospitalBuilding	1	0	0	0	0	1	0	1	1	1
Kitchen	1	0	0	0	0	1	0	0	0	1
Laboratory	0	0	0	0	0	1	0	0	0	1
LivingRoom	0	0	0	0	0	1	0	0	0	0
Meadow	0	0	0	1	1	1	1	0	0	0
RestRoom	1	0	0	0	0	1	0	0	0	0
UrbanArea	0	0	0	1	1	1	1	1	1	0
Wood	0	1	1	1	1	1	1	0	0	0

Columns: 1=brushingTeeth; 2=hikingUp; 3=hikingDown; 4=ridingBycicle; 5=jogging; 6=standingStill; 7=strolling; 8=walkingDownstairs; 9=walkingUpstairs; 10=writingOnBlackboard

#### **Experimental setup**

- Data acquired from a GPS receiver and two *Sun SPOTs* 
  - Programmable in Java
    - Fully capable JME CLDC 1.1 Java VM
  - 180 MHz 32 bit processor, 512K RAM/4M flash memory, IEEE 802.15.4 radio
  - <u>http://www.sunspotworld.com</u>
- 5-hours activity data collected by 6 volunteers

• 10 activities



#### **Preliminary implementation**

#### • Experimental results

#### (a) Evaluation of statistical classifiers (b) Overall accuracy

Classifier	Accuracy
Bayesian Network	72.95%
C4.5 Decision Tree	66.23%
Multiclass Logistic Regression	80.21%
Naive Bayes	68.55%
SVM	71.81%

Classifier	Accuracy
statistical	80.21%
statistical-voted	84.72%
COSAR	89.20%
COSAR-voted	93.44%

#### (c) Error reduction

$versus \rightarrow$	statistical	statistical-voted	COSAR
statistical-voted	22.79%		
COSAR	45.43%	29.32%	
COSAR-voted	66.85%	57.07%	39.26%

#### Open issues and future work

• Coping with dynamic sensors configurations

- Automatically deriving fuzzy assertions
- Recognizing concurrent and interleaved activities
- Preserving users' privacy
- Devising effective activity-aware applications

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