Unsupervised Recognition of Interleaved Activities of Daily Living through Ontological and Probabilistic Reasoning

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MOTIVATION
Scenario

Recognizing activities of daily living in a smart-home to support healthcare, home automation, a more independent life, ...

We rely on unobtrusive sensors ...
State of the Art and Open Issues

Most activity recognition systems rely on ...

... supervised-based approaches:
- acquire expensive labeled data sets
- often user/environment-specific

... knowledge-based approaches:
- unfeasible to enumerate all activity patterns

We propose an unsupervised method to recognize complex/interleaved ADLs

Based on hybrid ontological – probabilistic reasoning
Our approach ...

... overcomes drawbacks of supervised-based approach not user/environment-specific, no expensive data set, ...

... relies on semantic relations (activities↔ events)

derived from ontological reasoning

... recognizes interleaved activities

... inferred by a probabilistic model
MODEL AND SYSTEM
System overview

1. Semantic correlation reasoner
2. Statistical analysis of events
3. Markov Logic Network (MLN) / MAP Inference

MLN knowledge base

Event(se1,et1,t1)

semantic correlations

Recognized activity instances

Semantic integration layer

Semantic correlation reasoner
1. Semantic Correlation Reasoner

Why do we use Ontology (OWL2)?

- to derive semantic correlations (event type ↔ activity class)

### Ontology / Axioms

- Ontology 
- Axioms

OWL2 Reasoner infers

{turn on stove} is a predictive sensor event type for {Prepare hot meal} and {Prepare tea}

### PPM Matrix

<table>
<thead>
<tr>
<th>PPM Matrix</th>
<th>stove</th>
<th>silverware_drawer</th>
<th>freezer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hot meal</td>
<td>0.5</td>
<td>0.33</td>
<td>0.5</td>
</tr>
<tr>
<td>Cold meal</td>
<td>0.0</td>
<td>0.33</td>
<td>0.5</td>
</tr>
<tr>
<td>Tea</td>
<td>0.5</td>
<td>0.33</td>
<td>0.0</td>
</tr>
</tbody>
</table>

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2. Statistical Analysis of Events

**Input:** PPM matrix and temporally ordered events

- infers most probable activity class for each event
- allows to define activity boundaries (activity instance candidate)

Our ontology is translated into the \( \text{MLN}_{NC} \) model
3. MLN / MAP Inference

**Observed predicates**

- Freezer
  - 0.5: hot meal
  - 0.5: cold meal
  - 0.0: tea

- Stove
  - 0.5: hot meal
  - 0.0: cold meal
  - 0.5: tea

**ADL**

- Hot meal?
- Cold meal?
- Tea?

**Event 1:** opens freezer (1:00pm)
**Event 2:** turns on stove (1:02pm)

**Hidden predicates**

- Sensor Event Freezer
  - Sensor Event Stove

- belong to ADL

- Hot meal
Data Sets

We consider two well-known data sets ...

1. CASAS (controlled environment)
   - Interleaved ADLs of twenty-one subjects
   - Sensors: movement, water, interaction, door, phone
   - Activities: fill medications dispenser, watch DVD, water plants, answer the phone, clean, choose outfit, ...

2. SmartFaber (uncontrolled environment)
   - An elderly woman diagnosed with Mild Cognitive Impairment
   - Sensors: magnetic, motion, presence, temperature
   - Activities: taking medicines, cooking, ...
CASAS (1/2)

- Our approach outperforms HMM
  ontological reasoning is effective

- Refinement improves boundary precision

![Graph showing F-Measure and Minutes for different acs (ac1 to ac8)]

- MLN_{NC} (Dataset)
- MLN_{NC} (Ontology)
- HMM (related work)

- Candidate
- Refined

![Graph showing Delta-Start and Delta-Dur for F-Measure and Minutes]
SmartFaber (2/2)

- unsupervised and supervised-based results are comparable
- results were penalized by a poor choice of sensors

![Graphs showing F-Measure and Minutes for Delta-Start and Delta-Dur](image)

- MLN$_{NC}$ (Dataset)
- MLN$_{NC}$ (Ontology)
- Supervised / SmartFarber
- Candidate
- Refined
DISCUSSION / FUTURE WORK
Discussion

Results with two large datasets of interleaved ADLs were positive, but...

- ... knowledge engineering is required (build ontology)

  existing smart-home ontologies can be reused

- ... it is questionable if one ontology can cover every home

  adaptation/extension should be performed (semi-) automatically
Future Work

Extensive real-world experiments should show ...

... if and how the ontology has to be adapted

... what happens in a multi-user environment

Can active learning allow to ...

... fine-tune existing models? (user’s environment/habits)

... evolve the ontology according to the current context?
THANK YOU FOR YOUR ATTENTION
BACKUP SLIDES
Semantic Integration Layer

- collects events data from a sensor network
- applies preprocessing rules to detect operations

Example

fridge door sensor signaled “1”

→

the operation is “opening the fridge”

<Event(se₁, et₁, t₁), ..., Event(seₖ, etₖ, tₖ)>
MLN Model (detailed)

PPM Matrix
- *PriorProbability

Statistical analysis of events
- *InstanceCandidate / *Event

Hidden predicates

Observed predicates

*PriorProbability
(SenEvent, ADL, ActivClass, p)

*Event
(SenEvent, EventType, Time)

*InstanceCandidate
(ADL, Start, Stop)

Occurrences
(SenEvent, ADL)

InstanceClass
(ActivClass, ADL)

Ontological constraints

time-aware inference
temporal
knowledge-based

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