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CoCAPS: Design low-cost sensors to provide rich information about the behavior of the person (s) inside a building in the service of energy efficiency and autonomy

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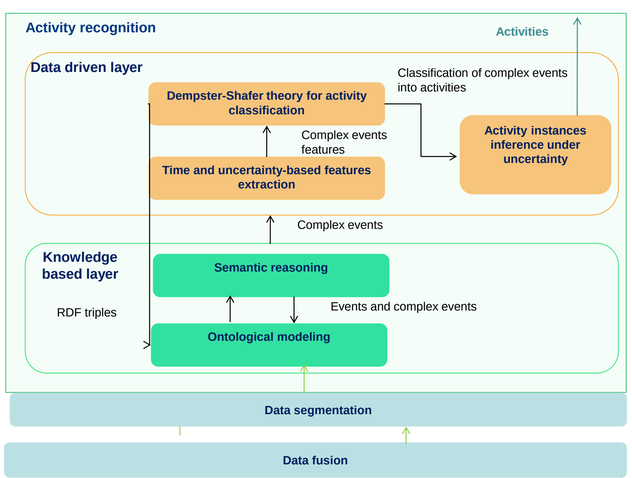
Context and Motivation

- Intelligent real-time decision making in smart spaces (office, home, etc.)
  - For: action decision based on user activities, etc.
  - From: Multiple types of sensors (motion, temperature, RFID, etc.) that may be imperfect
  - To: Provide better life quality for dependent person (e.g. elderly), services for energy management, etc.

Challenges

- How to recognize human activities by combining statistic learning (probabilistic model) and symbolic reasoning (automated reasoning, ontologies) using imperfect data?
- How To fusion heterogeneous data and compute their uncertainty ?

Contribution 1: AGACY Monitoring hybrid method for activity recognition



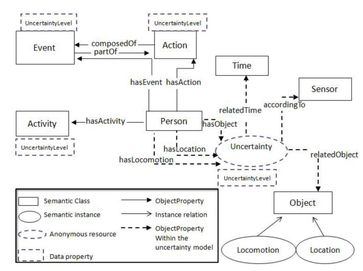
Activity Recognition Architecture

Knowledge based layer

Semantic Reasoning & Ontological modeling

$\forall$ se_1, $se_2 \in \{Sensors\}$, t_1, $t_2 \in \{Time\}$, and $p \in \{Person\}$
(p hasLocomotion [a Uncertainty; uncertaintyLevel n_1; relatedObject SitOn; relatedTime t_1; accordingTo se_1]
$\wedge$
(p hasObject [a Uncertainty; uncertaintyLevel n_2; relatedObject Chair; relatedTime t_2; accordingTo se_2])
$\longrightarrow$ ev(SitOnChair, max(t_1,t_2), min(n_1, n_2))

Example of rule for inferring the event instance sitOnChair



Data driven layer

- Time & uncertainty–based features extraction: computes the feature weight based on the uncertainty values of the actions and their time occurrence
- Application of The Dempster-Shafer theory (DS) for activity classification and the calculus of their uncertainty values
- Smart aggregation under uncertainty: improvement of previous algorithm for activities instances inferring by including the uncertainty of the activities in the process

Contribution 2: Data Fusion

PROBLEM FORMULATION

- For the aim of activity recognition, we divide the area into zones of interest where the person will be localized by providing probability of presence over all zones.
- The shape of each zone can change from a sensing modality to another, but both should cover the same activity area (e.g. the shape of zone 9 is different, Fig.01 and Fig.02, but both of them covers the table).

METHODS

- To reduce the impact of sensor faults, we use a filtering algorithm which combines the prediction, computed using a human motion model and previous results, with the observation computed using the sensors data [10].
- To further handle uncertainty between zones, we enhance the filtering by using the Transferable Belief Model [11].
- To detect state changes, e.g. distinguish between a second person and a sensor fault, we can leverage the conflict as used in dynamic objects detection [12].

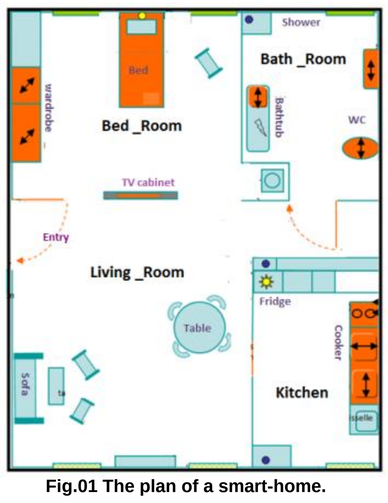


Fig.01 The plan of a smart-home.

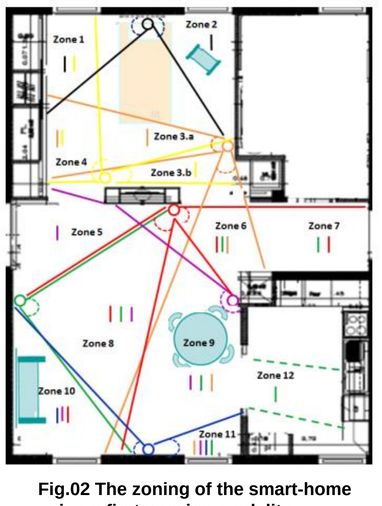


Fig.02 The zoning of the smart-home using a first sensing modality

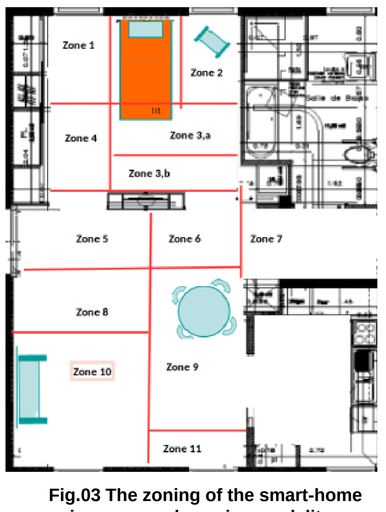
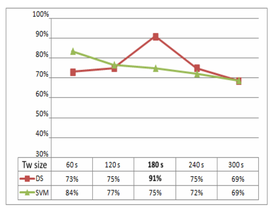


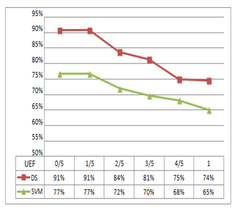
Fig.03 The zoning of the smart-home using a second sensing modality

Experiments

1) Evaluation of activity recognition with OPORTUNITY dataset



Precision values by varying the time window size



Precision values by varying the number of uncertain sensor data

SVM	AGACY Monitoring
75%	90%

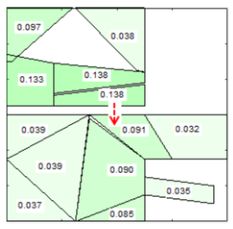
Precision of SVM et AGACY Monitoring for activity recognition using Opportunity dataset

2) Data fusion

- When the person transits from A zone to another, as shown With the red arrow, the method Of [11] is better thanks to TBM.

[11]	[10]
13%	26%

Localization errors rate over the same scenario.



Results from method [11].

Results from method [10].

Publications

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