

Ambient Assisted Living: Fuzzy Logic & Stochastic Modelling

Tommaso Papini

STLab, Department of Information Engineering, University of Florence, Italy,
tommaso.papini@unifi.it

29th June 2017

- ▶ Ambient Assisted Living
- ▶ Activity Recognition
 - ▶ A Fuzzy Logic approach
 - ▶ A Stochastic Model approach
- ▶ A joint proposal

Overview

Ambient Assisted Living

- Problem description
- Annotated datasets

A Fuzzy Logic approach

- Linguistic terms & membership functions
- Intersection membership function
- Rule-based inference engine

A Stochastic Modelling approach

- Process mining
- Possible analyses
- H-MRGP-M

A joint proposal

- Pros & cons
- Proposals

Ambient Assisted Living

Ambient Assisted Living

Ambient Assisted Living is a research area that aims to help those people living within *smart environments* (i.e., provided with sensors and actuators) exploiting sensors and data processing technology.



Objectives

A *smart environment* is a **partially observable** system:

- ▶ the actual state of the system is hidden;
- ▶ only events are observables (*observations*) as they are emitted by the system (e.g. the activation of a sensor).

Main analyses of interest:

- ▶ **Diagnosis:** (a.k.a. Activity Recognition, AR) esteem the actual present state of the system from the events observed.
- ▶ **Prediction:** esteem what's going to be the actual system's state after a certain amount of time or the probability density function that a certain event happens.
- ▶ **Action scheduling:** chose the best action and when to execute it in order to avoid critical situations.

Online analysis:

- ▶ analyse the system *while* it is evolving.

Activity Recognition

Activity Recognition techniques can be divided into two classes:

- ▶ **Knowledge-Driven Approaches (KDA)**
 - ▶ domain-specific expert knowledge is used in order to build the AR model.
- ▶ **Data-Driven Approaches (DDA)**
 - ▶ a training dataset is used in order to automatically build the AR model, in a supervised fashion.

Comparative survey between AR researches:

- ▶ *STLab* research group¹
 - ▶ stochastic modelling techniques.
- ▶ *Sinbad*² research group²
 - ▶ fuzzy logic techniques and temporal window-based classification

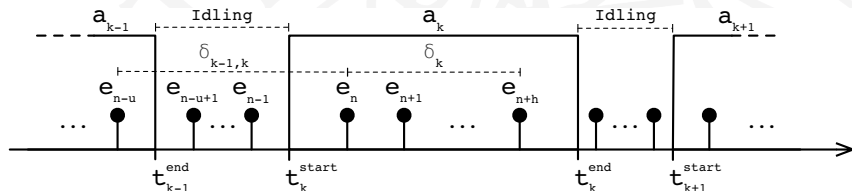
¹<https://stlab.dinfo.unifi.it/>

²<http://sinbad2.ujaen.es/>

Annotated datasets

An *annotated dataset* of a partially observable system is a dataset with:

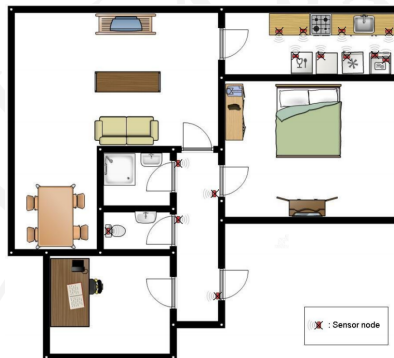
- ▶ recorded events and when each happened (timestamp);
- ▶ manual annotations of the evolution of the actual state of the system (with time intervals for each state).



Annotated datasets

van Kasteren

A classic example is the *van Kasteren*³⁴ annotated dataset for AAL



³<https://sites.google.com/site/tim0306/datasets>

⁴Van Kasteren, T., Noulas, A., Englebienne, G. and Kröse, B., 2008, September. Accurate activity recognition in a home setting. In Proceedings of the 10th international conference on Ubiquitous computing (pp. 1-9). ACM.

Annotated datasets

van Kasteren

- ▶ 7+1 types of activities (Activities of Daily Living, ADL⁵):
 - ▶ {Leaving house, Preparing a beverage, Preparing breakfast, Preparing dinner, Sleeping, Taking shower, Toileting} \cup {Idling}.
- ▶ 28 types of events (on/off of 14 sensors):
 - ▶ toilet door open/closed, fridge open/closed,
- ▶ 28 days of events and annotated activities:
 - ▶ 245 activities, annotated through a Bluetooth device with voice recognition;
 - ▶ 219 *Idling* intervals;
 - ▶ 2638 observed events.

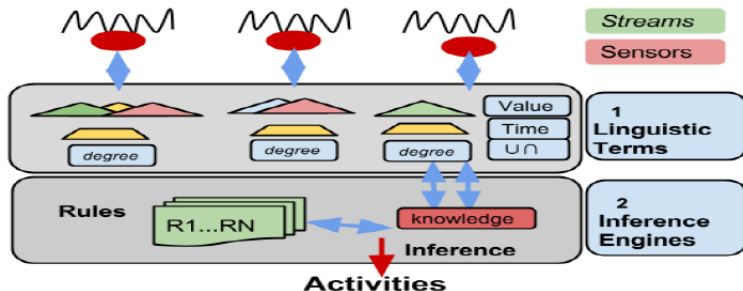
⁵Katz, S., Downs, T.D., Cash, H.R. and Grotz, R.C., 1970. Progress in development of the index of ADL. The gerontologist, 10(1 Part 1), pp.20-30.

A Fuzzy Logic approach

A Fuzzy Logic approach

A Knowledge-Driven Approach for Activity Recognition:⁶

- ▶ expert knowledge to define **time** and **sensor-specific fuzzy sets**;
- ▶ expert knowledge to define **classification fuzzy rules**.



⁶Medina, J., Espinilla, M., Moya, F., and Nugent, C. Activity recognition by means of rule-based inference engine based on fuzzy linguistic approach. In 13th Scandinavian Conference on Artificial Intelligence Halmstad (November 2015 2015).

Definitions

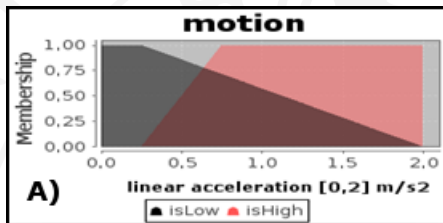
- ▶ Each sensor j has an associated sensor stream s^j ;
- ▶ sensor stream $s^j = \{m_i^j\}$ set of measures;
- ▶ measure $m_i^j = \langle v_i^j, t_i^j \rangle$;
 - ▶ measure value v_i^j ;
 - ▶ measure timestamp t_i^j .

Linguistic terms & membership functions

Sensors

For each sensor s^j , we define:

- ▶ a fuzzy linguistic variable (e.g. *Motion*);
- ▶ the linguistic terms (e.g. *High* and *Low*);
- ▶ their membership functions $\mu_V(v_i^j)$
 - ▶ degree of membership of the measure value v_i^j in the fuzzy set V .

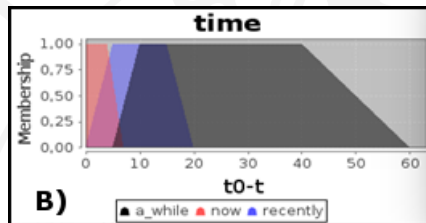


Linguistic terms & membership functions

Time

For the time dimension (only once), we define:

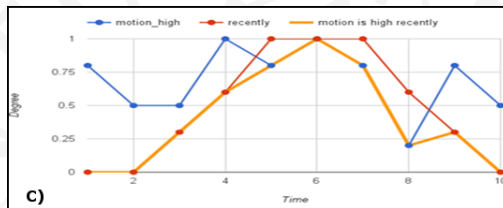
- ▶ the fuzzy linguistic variable *Time*;
- ▶ three linguistic terms *Now*, *Recently* and *aWhile*;
- ▶ their membership functions $\mu T(t_i^j)$
 - ▶ degree of membership of the measure timestamp t_i^j in the fuzzy set T .



Intersection membership function

For each sensor and time linguistic term, we define the intersection membership function:

- ▶ $V \cap T(m_i^j) = V(v_i^j) \cap T(t_i^j)$
 - ▶ t-norm $\cap = \text{MIN}$;
- ▶ e.g. *High_motion Recently*.



The degree of membership of all measures $\{m_i^j\}$ of a sensor s^j to $V \cap T$ is given by aggregation through union:

- ▶ $V \cap T(s^j) = \bigcup_{m_i^j \in s^j} V \cap T(m_i^j)$

Rule-based inference engine

A domain expert gives temporal fuzzy rules, through which linguistic terms from multiple sensors can be processed.

Fuzzy temporal logic rules have the form:

IF v is V WHEN t is T THEN m IS M

For example:

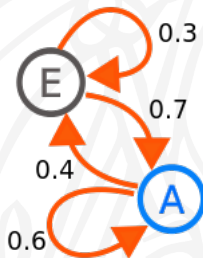
IF (movement IS significant AND inhabitant IS close to living room) WHEN now AND (inhabitant IS cooking) WHEN a while THEN inhabitant IS eating

A Stochastic Modelling approach

Stochastic Models

Stochastic Models represent an approximation of systems where are modelled:

- ▶ the evolution of the system's state;
- ▶ the stochastic parameters that characterize how the system passes from a state to another.



Process mining

From annotated datasets to stochastic models

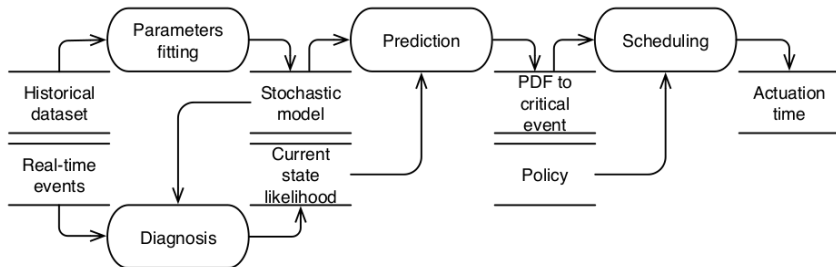
The term **process mining** indicates a set of techniques for building a stochastic model of a partially observable system from an annotated dataset of that same system.

Process mining is composed of two main techniques:

- ▶ **Process elicitation:** builds the discrete model (i.e., with no information about the sojourn times in different system's state) from events and annotated activities in the dataset.
- ▶ **Process enhancement:** adds a continuous time vision to the discrete model introducing stochastic parameters that describe how the system evolves during time, using statistical measures calculated from the dataset.

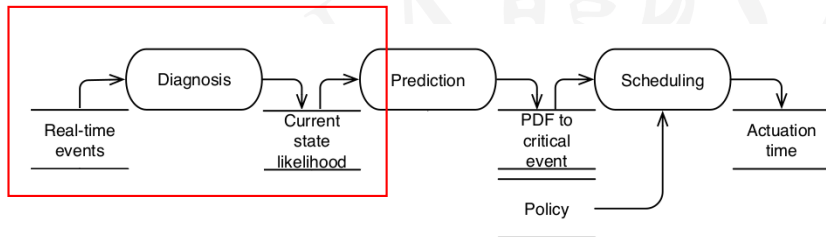
Smart environments analyses

General schema



- ▶ **Process mining**: from annotated datasets to stochastic model.
- ▶ **Diagnosis**: from actual events to likelihood of the current state (on a specific stochastic model).
- ▶ **Prediction**: from likelihood of the current state to probability that a critical event occurs.
- ▶ **Scheduling**: from probability that a critical event occurs to time when to schedule the response action (with a specific reaction policy).

Diagnosis



Diagnosis computes the most likely actual state of the model at present time, given all the events observed up until the present time.

H-MRGP-M

The **Hidden-Markov Regenerative Process-Model** (H-MRGP-M) has been developed by STLab at University of Florence.⁷

- ▶ Models the continuous sojourn time in the system's states and the events inter-times.
- ▶ The model's state evolves as a *Markov Regenerative Process* (MRP).

⁷Carnevali, L., Nugent, C., Patara, F. and Vicario, E., 2015, September. A continuous-time model-based approach to activity recognition for ambient assisted living. In International Conference on Quantitative Evaluation of Systems (pp. 38-53). Springer International Publishing.

H-MRGP-M

Statistical measures

- ▶ Experiments on the van Kasteren dataset.
- ▶ Starting from timestamps in the dataset, statistical measures are computed:
 - ▶ on the sojourn time in each activity;
 - ▶ of the inter-time between events in each activity.

	Sojourn time		Inter-time between events	
	μ (s)	CV	μ (s)	CV
Leaving house	40 261.455	1.042	9 354.190	2.810
Preparing a beverage	35.667	1.361	7.643	2.613
Preparing breakfast	108.684	0.713	9.928	1.844
Preparing dinner	1 801.889	0.640	77.966	2.589
Sleeping	26 116.571	0.442	1 871.836	3.090
Taking shower	485.910	0.298	102.788	1.969
Toileting	88.742	1.175	14.814	2.449

H-MRGP-M

Stochastic model @runtime

- ▶ The model is created with *process mining* techniques:
 - ▶ *process elicitation* in order to define the model topology;
 - ▶ *process enhancement* in order to add stochastic parameters from the statistical measures calculated (Whitt technique⁸ and software PhFit⁹).
- ▶ Model **@runtime**: the model is updated each time a new event is observed.¹⁰
- ▶ The model formalism used is that of **stochastic Timed Petri Net** (sTPN).^{11 12}

⁸Whitt, W., 1982. Approximating a point process by a renewal process, I: Two basic methods. Operations Research, 30(1), pp.125-147.

⁹Horváth, A. and Telek, M., 2002, April. Phfit: A general phase-type fitting tool. In International Conference on Modelling Techniques and Tools for Computer Performance Evaluation (pp. 82-91). Springer Berlin Heidelberg.

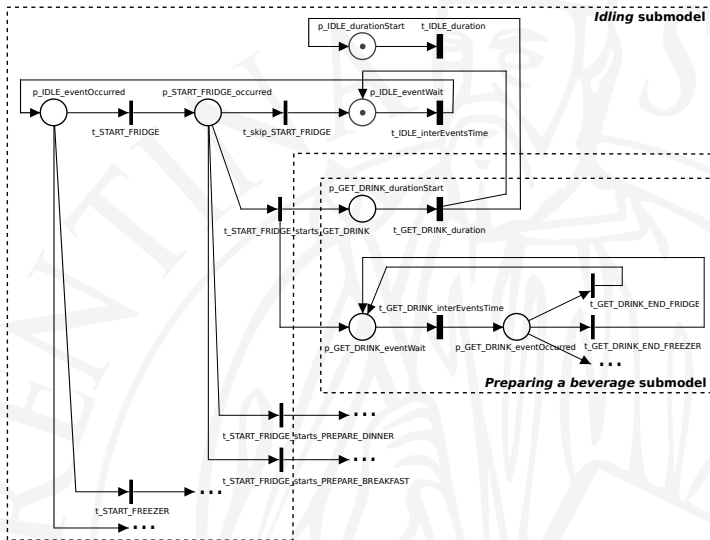
¹⁰Blair, G., Bencomo, N. and France, R.B., 2009. Models@ run. time. Computer, 42(10).

¹¹Horváth, A. and Vicario, E., 2009, September. Aggregated stochastic state classes in quantitative evaluation of non-markovian stochastic Petri nets. In Quantitative Evaluation of Systems, 2009. QEST'09. Sixth International Conference on the (pp. 155-164). IEEE.

¹²Vicario, E., 2001. Static analysis and dynamic steering of time-dependent systems. IEEE transactions on software engineering, 27(8), pp.728-748.

H-MRGP-M

sTPN

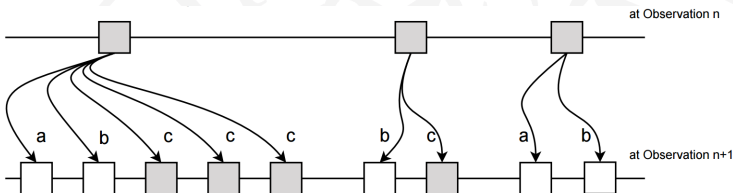


H-MRGP-M

Transient analysis

After each observation, likelihoods of being in different system's states can be computed up until the next observation.

- ▶ The transient analysis technique for MRP based on stochastic state classes is exploited.¹³



The state with highest likelihood is the diagnosed current activity.

¹³Horváth, A., Paolieri, M., Ridi, L. and Vicario, E., 2012. Transient analysis of non-Markovian models using stochastic state classes. Performance Evaluation, 69(7), pp.315-335.

H-MRGP-M

Transient analysis

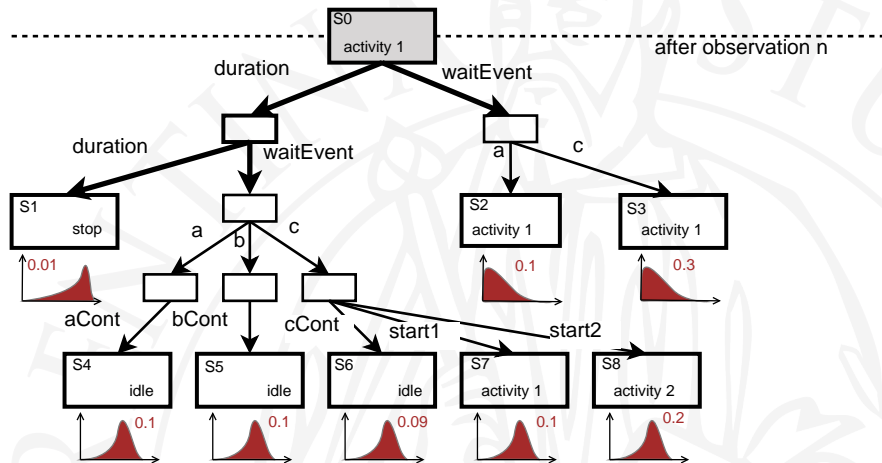


After having observed the event n , for each (possible) current activity

- ▶ a classes tree is built until the next observation (event $n + 1$) is met;
- ▶ leaves corresponding to the new observed event are selected;
- ▶ the PDF of the selected leaves is computed in the delay d (inter-time between events n and $n + 1$) in each tree and summing them with weight the root likelihood;
- ▶ the highest is given as most likely current activity.

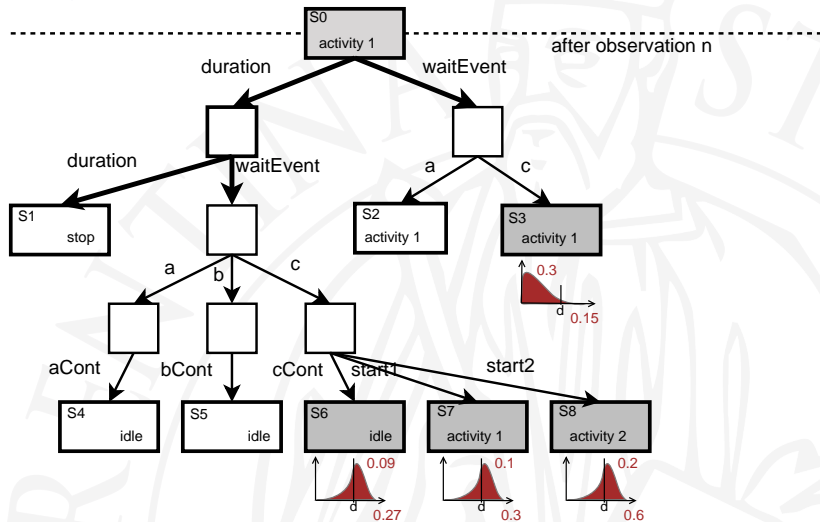
H-MRGP-M

Transient analysis



H-MRGP-M

Transient analysis



A joint proposal

Pros & cons

The H-MRGP-M model has several pros and cons.

Pros:

- ▶ DDA;
- ▶ accurate description of system evolution through stochastic modellization.

Cons:

- ▶ no support for continuous sensors;
- ▶ only last event taken into consideration.

Exploiting linguistic terms and temporal fuzzy rules, support for continuous sensors can be added to the H-MRGP-M model!

Proposal

Intersection fuzzy set

- ▶ Use linguistic variables as before:
 - ▶ provided by an expert;
 - ▶ one for the time dimension and one for each continuous sensor.
- ▶ Define state-changes for each continuous sensor:
 - ▶ for each pair of time and sensor-specific linguistic term define the intersection fuzzy set $V \cap T$;
 - ▶ each combination is seen as a different state-change for a specific sensor.
- ▶ The new state-changes of the continuous sensor are added to the model.

When a new continuous event is observed:

- ▶ compute the degree of membership of the new measurement to the intersection fuzzy sets $V \cap T$;
- ▶ identify the intersection fuzzy set with highest membership degree;
- ▶ the state-change corresponding to the fuzzy set with highest membership degree is fired in the H-MRGP-M model.

Proposal

Fuzzy temporal rules

- ▶ Use linguistic variables as before:
 - ▶ provided by an expert;
 - ▶ one for the time dimension and one for each continuous sensor.
- ▶ Define state-changes for each continuous sensor:
 - ▶ define state-change fuzzy temporal rules (by an expert);
 - ▶ each rule is applied to the whole sensor data stream;
 - ▶ e.g. *IF (movement IS high) WHEN now AND (movement IS low) WHEN a while THEN inhabitant IS started moving.*
- ▶ The new state-changes of the continuous sensor are added to the model.

When a new continuous event is observed:

- ▶ infer the state-change using the fuzzy temporal rule engine and the sensor data stream;
- ▶ the inferred state-change is fired in the H-MRGP-M model.

Future proposals

- ▶ Full DDA:
 - ▶ extended belief rule-based inference;¹⁴
 - ▶ ANFIS.
- ▶ Sensor-specific time linguistic terms:
 - ▶ each sensor might have different variation distributions in time;
 - ▶ e.g. a sensor motion might have very rapid and very high variations, while a temperature sensor is usually smoother.

¹⁴Espinilla, M., Medina, J., Calzada, A., Liu, J., Martínez, L. and Nugent, C., 2016. Optimizing the configuration of an heterogeneous architecture of sensors for activity recognition, using the extended belief rule-based inference methodology. Microprocessors and Microsystems.

The end.



Questions? Thanks!