Pervasive informatics and persistent actimetric information in health smart homes: different approaches

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Introduction

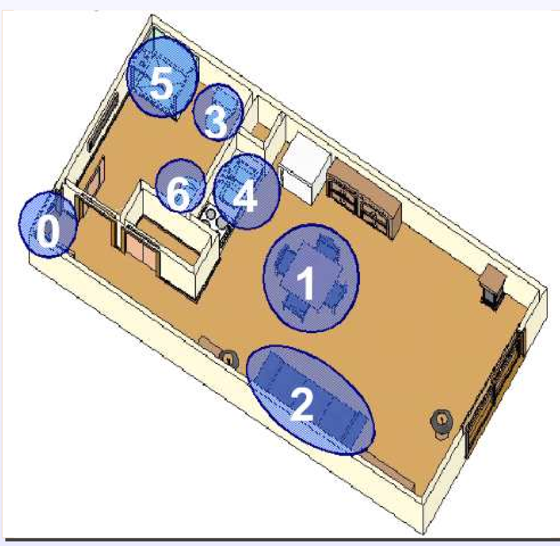
This paper discuss the ability to obtain a reliable pervasive information at home from a network of localizing sensors allowing to follow the different activity-station at which a dependent (elderly or handicapped) person can be detected. Since 12 years ([1-3]), many experiments have been achieved for watching dependent people at home, in particular elderly and handicapped persons. For acquiring data necessary to permit the alarms triggering, numerous sensors have been invented, in particular for localizing the person at home or in the surroundings. These localizers are on the body (GPS, accelerometers, etc.), in the flat rooms (on the walls: infrared or radar detectors; on the ground, the bed or the chairs: pressure sensors), on the doors (magnetic switches) or in gardens and streets (video-cameras).

- Context
  - pervasive watching systems for Health Smart Homes
  - detection of neuro-degenerative diseases (*e.g.*: Alzheimer) or post-brain stroke disorders
  - evaluation and prolongation of elderly persons autonomy
- Goals
  - model of elderly persons activity in Health Smart Homes
  - evaluation of actimetric perseveration
  - activity prediction in order to detect variation in their comportment, trigger alarms or diagnosis autonomy

Method: Corpus Acquisition

The data recorded can be treated as time series as the sequence of color coding numbers of balls (symbolizing activity-stations) taken in a Polya's urn, in which the persistence of the presence in an activity-station is represented by adding a number of balls of the same color as the ball just drawn ([5]). The sequence could also represent historical data from a model, deriving from language models and markovian processes existing in speech recognition research, where the persistence is the probability to stay at the same activity-station ([6]). Other models can also be used as well as the mean time passed or the remaining time in the activity-station. Theses models are compared in order to use the most representative one. The best procedure will be used to trigger alarms, which will occur when an incorrect prediction is made, or when the person persists at the same station more than the mean time passed in this station.

- 2x: 22/03/2005 → 24/01/2006 (10 month) + 18/07/2007 → 15/01/2008 (6 month)



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Day	Month	Year	Hour	Minute	Second	activity-station-code
24	03	2005	17	37	36	1
24	03	2005	17	37	37	2
24	03	2005	17	37	38	2
24	03	2005	17	37	40	1
24	03	2005	17	37	48	1
24	03	2005	17	37	49	4
24	03	2005	17	37	50	4
24	03	2005	17	37	51	1
24	03	2005	17	37	53	4
24	03	2005	17	37	54	4
24	03	2005	17	37	55	4
24	03	2005	17	37	56	2
24	03	2005	17	37	57	2

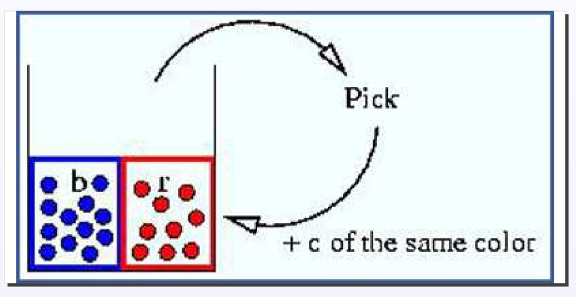
- Time series transformation: $s\ \overbrace{2\,2\,2\,\ldots\,2\,2}^{x \text{ times}}\ \overbrace{3\,3\,3\,\ldots\,3\,3}^{y \text{ times}}\ 4\,4\,4\,\ldots\,e$

Since s the beginning of the day, the person was in her bedroom (2).

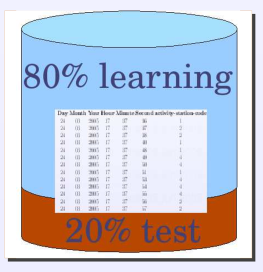
After x seconds, she's gone to the toilets (3) during y seconds, then in the kitchen (4)…until the end of the day e.

Polya's urns

- Context
  - probabilistic models derived from urns ones
- Main idea
  - color codes ≡ pertinent locations for the watching
  - succession of these colors considered as balls taken from a Polya's urn
  - persistence in task $i \equiv +\, k_i(t)$ balls of color i when a ball of color i has been taken at time t



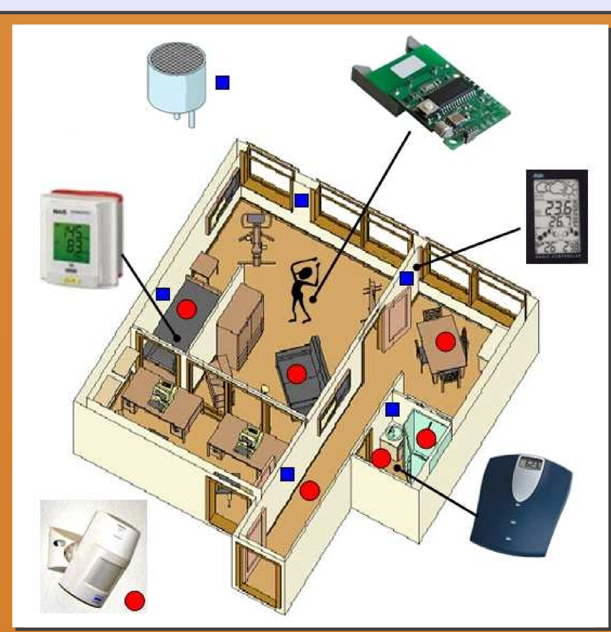
- Results
  - Corpus: 80% for learning, 20% for test



  - Good prediction rate with smoothing techniques: **60.24%** with adding 1 ball
- Discussion
  - The observed activity at time t is depending on the whole past (since a reset supposed to be made at the beginning of each day)
  - The number of balls to add is hard to calculate
  - This calculation must be improved

Mean of Time passed

- Context
  - statistical models
- Main idea
  - mean of time passed in each activity
  - persistence in task $i \equiv$ time passed in $i >$ mean
- Results
  - Corpus: 80% for learning, 20% for test
  - Good prediction rate with smoothing techniques: **98.25%**
- Discussion
  - No prediction when time passed in $i >$ mean
  - Results denote overtraining



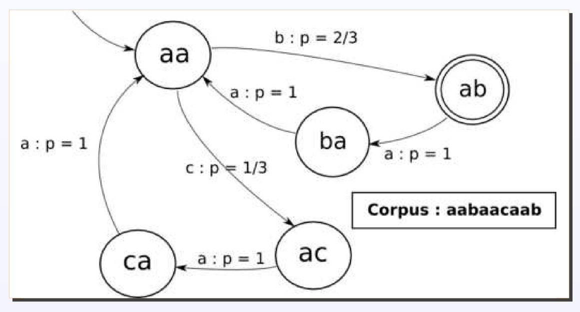
Discussion (all)

- day of week is an important factor of variation
- smoothing by taking the most frequent data from the learning window
- watching each 1mn historic data instead of each 1s

We should go further with a more continuus approach considering day of week, day of month,etc.

N-grams

- Context
  - stochastic models derived from Markovian ones
  - used in other domains: language model in speech recognition, dialog model, etc.
- Main idea
  - $n-1$ last elements used to predict the n-th
  - most probable element: $a_i = argmax_a P(a|a_{i-1}, a_{i-2}\ldots, a_{i-n+1})$
  - persistence in task $i \equiv$ probability p_{ii} of taking a ball of color i after a ball of color i



- Results
  - Corpus: 80% for learning, 20% for test
  - Good prediction rate (%) depending on day of week.

n	sun	mon	tue	wed	thu	fri	sat	total
1	51.60	47.34	42.61	46.25	58.50	52.73	45.79	48.88
2	97.05	97.49	**98.03**	97.65	**97.28**	**97.10**	**97.22**	**97.36**
3	97.05	**97.49**	98.03	**97.65**	97.27	97.09	97.22	97.36
4	97.05	97.49	98.03	97.65	97.26	97.09	97.21	97.36
5	**97.05**	97.48	98.02	97.65	97.26	97.09	97.21	97.36
6	97.03	97.47	98.01	97.64	97.25	97.08	97.21	97.36
7	97.03	97.46	98.00	97.63	97.25	97.06	97.20	97.35
8	97.01	97.45	97.99	97.62	97.24	97.04	97.18	97.35
9	97.01	97.44	97.97	97.60	97.23	97.01	97.17	97.34
10	96.98	97.42	97.96	97.58	97.20	96.99	97.16	97.33

  - Good prediction rate with smoothing techniques:
    - Without historic ($n = 1$): 60.25%
    - With an historic of 1 ($n = 2$): **98.24%**
    - $n = 2 \equiv$ the last second is sufficient to predict the next one
- Discussion
  - The dependency of the future of t lies only through the present time t
  - The most simple to develop, the most effective
  - Best results with $n = 2$ (historic of 1)

Conclusion

The sensors network is very important to follow up the dependent people during their walk trajectories inside home or outside. If the space/time data are acquired on healthy elderly people or on patients which suffer from neuro-degenerative diseases, the sensors recording must be very well calibrated, to give birth to specific profiles concerning the time series which correspond to the successive locations of the dependent person in rooms inside the flat or in specific places inside a room ([4]). Simpler than Polya's urns derived approach, the Markovian approach seems to be a good way of location modeling. Other models need to be improved in order to concurrence it. A big hope comes from the ambient information techniques to be able to detect a sudden fall on the ground or a progressive stereotyped behavior (for the early diagnosis of chronic neuro-degenerative diseases like the Alzheimer or Parkinson ones).

- Model of a human agent in Health smart home
- Algorithms which permit to understand the evolution of the data, represent at most person's activity, its habits and its deviations from these and identify change stereotyped, sudden or more chronic, of the behavior of the person
- perseveration parameters seems to be good indicators
- stochastic approaches looks promising (98,24% using the last second & smoothing techniques)

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