Multisensor Fusion for Monitoring Elderly Activities at Home

January 25, 2010

40 ans la révolution de l'information

INSTITUT NATIONAL DE RECHERCHE EN INFORMATIQUE ET EN AUTOMATIQUE

INRIA

centre de recherche SOPHIA ANTIPOLIS - MÉDITERRANÉE

Presented by : Nadia Zouba Valentin

PULSAR team

Supervisor : Monique Thonnat

Co-supervisor : François Bremond

Outline

1. Introduction
2. State of the art
3. Approach overview
4. Video analysis
5. Sensor analysis
6. Event recognition
7. Multisensor event fusion
8. Evaluation and results
9. Conclusion and future work

Introduction

- In 2035: 1/3 of Europeans more than 65 years
- 40% of people 65 and older have a disability
- Over 20% require continuous monitoring

Increasing number of high risk population (elderly, people with illness, …) living alone at home

Activities of Daily Living (ADLs)

Daily activities at home are activities that people tend to do everyday

Examples of daily activities:

- *Preparing meal (in kitchen) (11h– 12h)*
- *Eating (in dinning room) (12h -12h30)*
- *Resting, watching TV (in living room) (13h– 16h)*

Introduction: motivations

Increase independence and quality of life

- Enable elderly to **live longer** in their own home
- Maintain **autonomy** of elderly
- Reduce **costs** for public health systems
- Relieve **family** members and caregivers

ADLs monitoring at home

- Detect **alarming** situations (e.g. falling down)
- Calculate the **degree** of **frailty** of elderly people
- Detect **changes** in behavior

Introduction: objectives

Propose a **new cognitive vision approach** using ambient sensor technologies to recognize interesting activities at home;

Based on multisensor analysis and human activity recognition, it consists in:

- Detecting people
- Tracking people as they move
- Recognizing postures and activities of interest

Two main hypotheses have been considered

1- Fixed video cameras:

- Video cameras are fixed on a wall without pan, tilt and zoom

2- Monitoring one individual:

- One elderly person living alone in his/her own home is monitored

State of the art: sensing modalities

Fixed On

The Environment

- Motion sensors
- Contact sensors
- Water sensors
- Presence sensors
- Light sensors
- Electrical sensors
- Video sensors
- Audio sensors

The Person

- Heart Rate
- Pulse Oxymeter
- ECG
- EEG
- Accelerometers
- Pressure sensors

To Identify

Location

Interaction with Household Objects

Amount of Movement

Biomedical Function

Activities Performed

Health and Wellbeing's

State of the art: industrial systems for monitoring ADLs

QuietCare system [Glascock and Kutzik, 2006]

- Wireless motion sensors
- Learns the daily living activities of elderly
- Detects only motion

“I-pot” system [ipot, 2005]

- Electrical kettle
- Detects a sudden change in an elderly person’s tea habits
- Detects only one activity

Social alarms “Vivago system” [Sarela et al., 2003]

- Long-term monitoring of circadian rhythm
- 27-40% of users do not wear the alarm device on daily basis

State of the art: research projects for monitoring ADLs

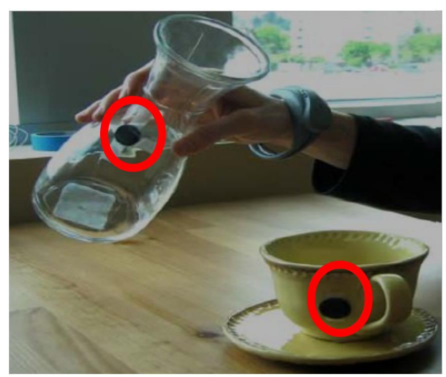
Wearable and environmental sensors

RFID glove [Philipose et al., 2004]

- RFID: Radio Frequency Identification

RFID bracelet [Tapia et al., 2006]

- Good recognition of several human activities
- Need to wear a glove or a bracelet
- All objects have to be tagged (lot of sensors are needed: > 100)



State of the art: research projects for monitoring activities

Video cameras

Probabilistic and stochastic approaches: (e.g. NNs, HMM, …)

- + Easy to implement using HMM
- - Difficult to modify or to add a priori knowledge

Assist person with dementia using video camera [Hoey, et al. ICVS 2007]

- + Good recognition of hand washing activity
- - Limited variety of activities

Constraints resolution approaches: [Vu, et al. IJCAI 2003]

- For video surveillance applications (e.g. metro station)
- + Based on video event models and spatio-temporal constraints
- - Support only video cameras (recognize only video events)

Approach overview

The proposed approach

- Based on an **extended constraint resolution** method:

+ Recognize multisensor activities with spatio-temporal constraints (support video and non video sensors)

+ Recognize ADLs (healthcare applications)

Main characteristics of the approach:

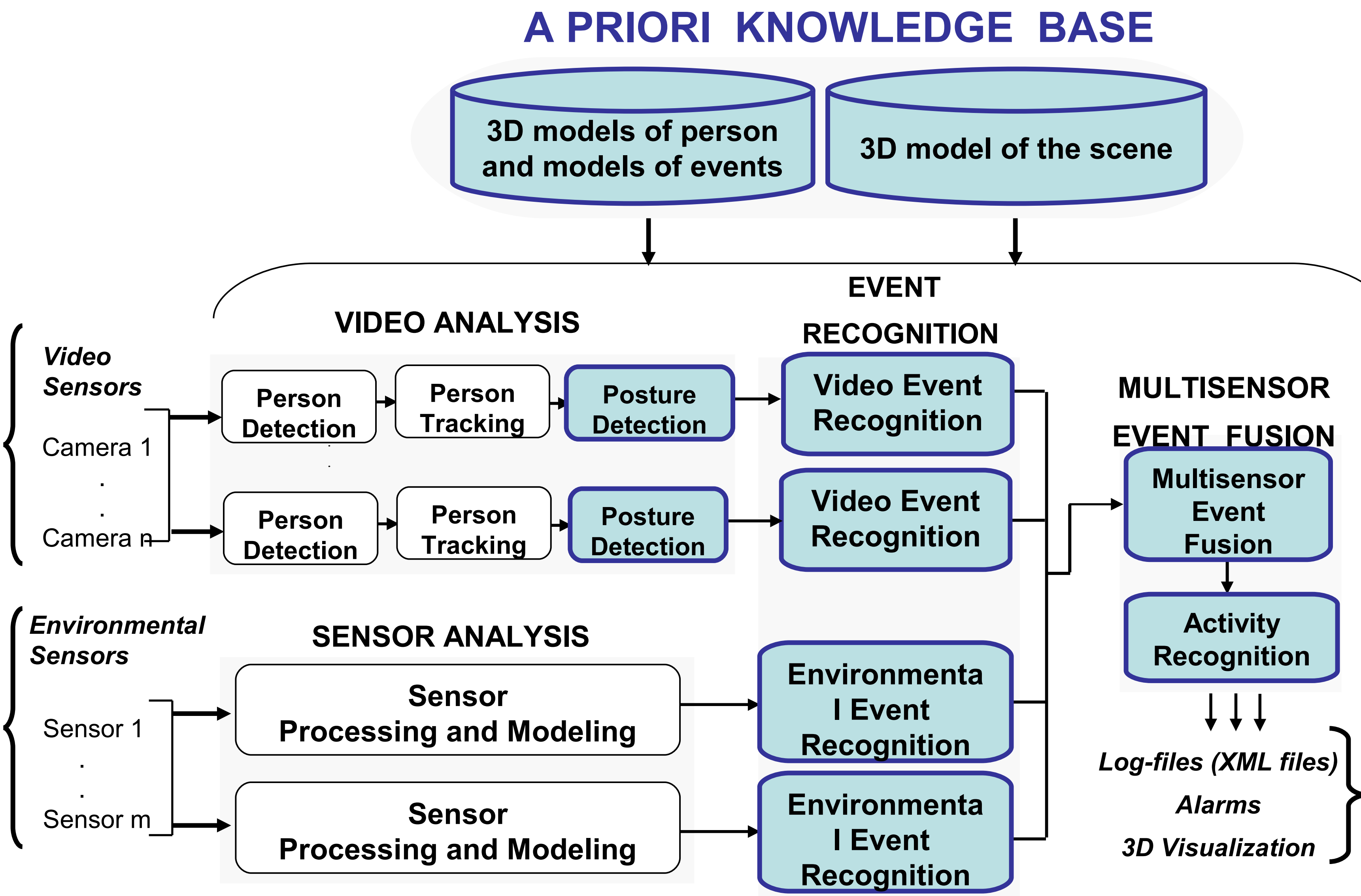
+ **No wearable sensors**: the elderly do not wear the device

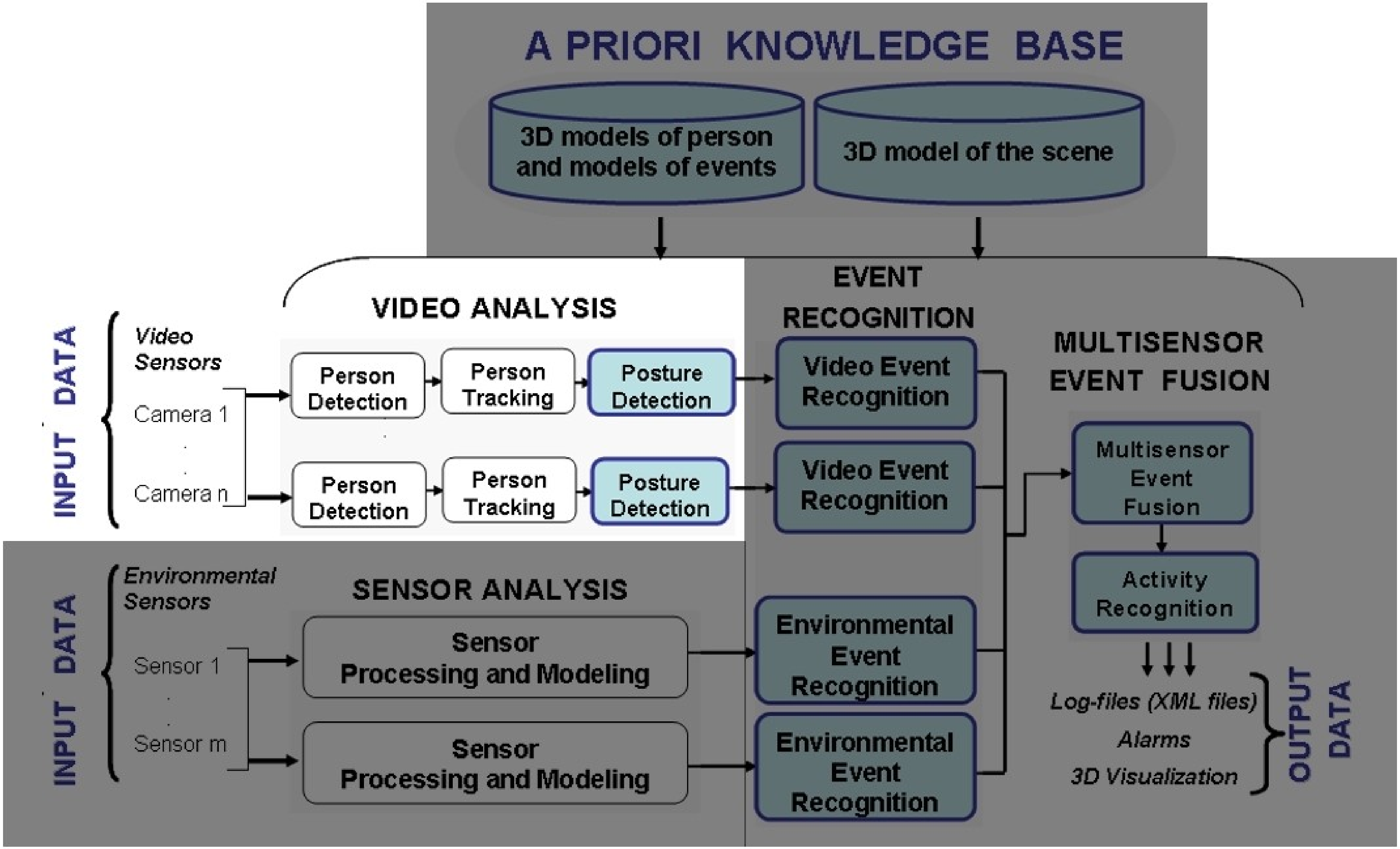
+ **Few sensors**: 28 sensors vs. 100 sensors for [Philipose et al., 2004] and [Tapia et al., 2006]

+ Only **house furniture were equipped** with sensors

+ **More than one activity** at home: 100 vs. 1 for [Hoey et al. 2007]

Approach overview (2)





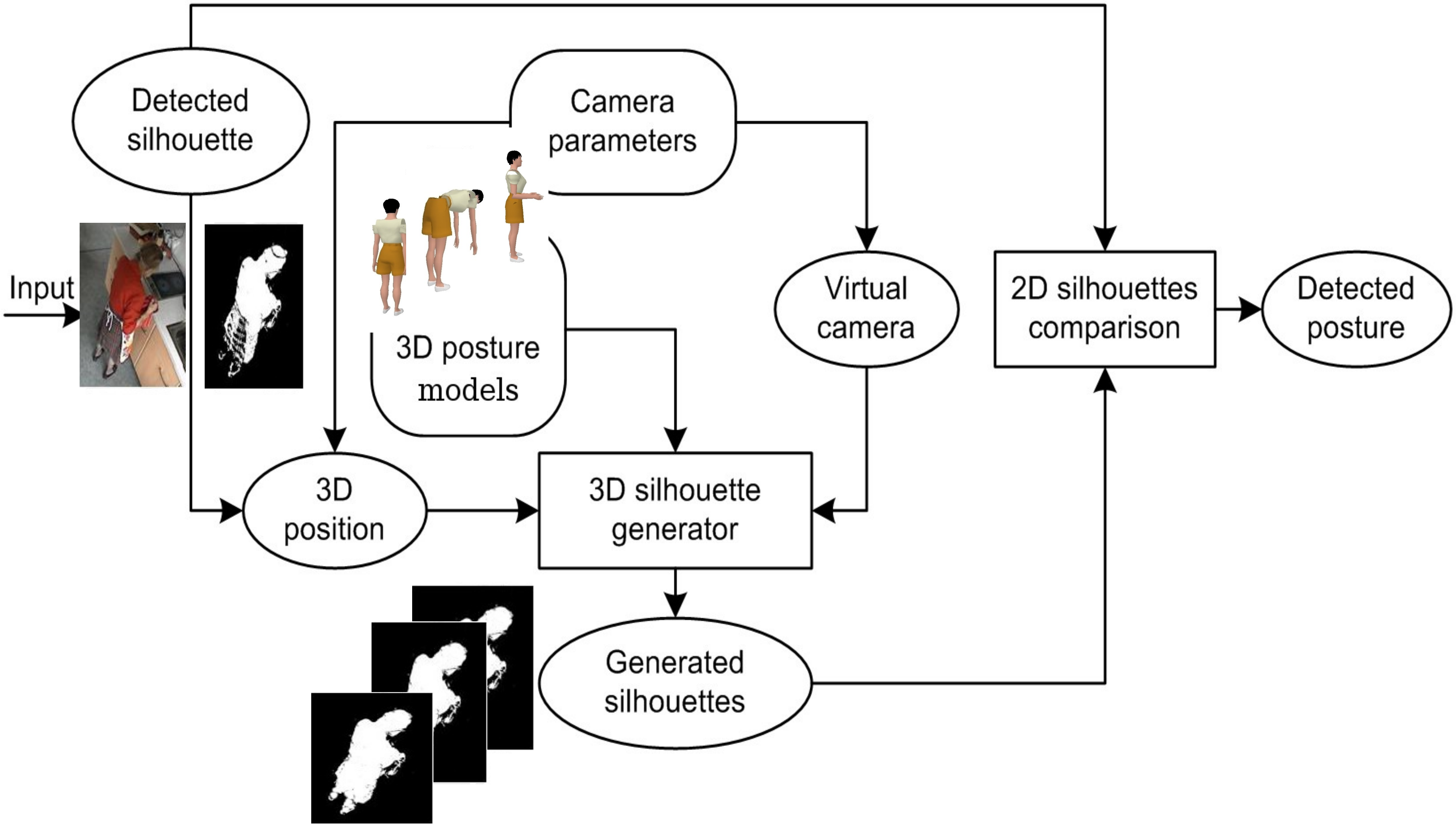
A PRIORI KNOWLEDGE BASE
3D models of person and models of events
3D model of the scene
VIDEO ANALYSIS
EVENT RECOGNITION
MULTISENSOR EVENT FUSION
INPUT DATA
Video Sensors
Camera 1
Camera n
Person Detection
Person Tracking
Posture Detection
Video Event Recognition
Multisensor Event Fusion
Activity Recognition
INPUT DATA
Environmental Sensors
Sensor 1
Sensor m
SENSOR ANALYSIS
Sensor Processing and Modeling
Environmental Event Recognition
Log-files (XML files)
Alarms
3D Visualization
OUTPUT DATA

Video analysis

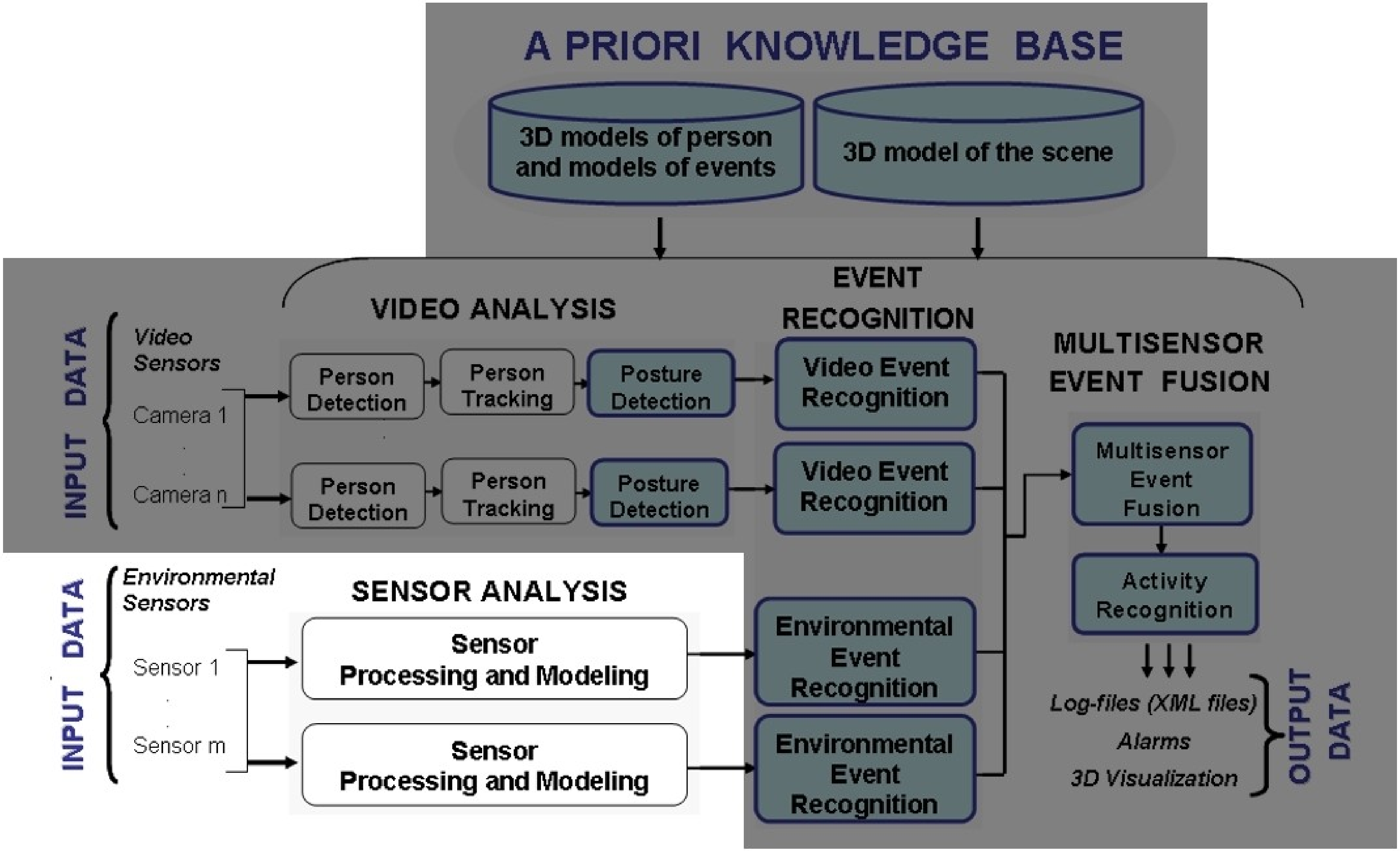
Input: video stream
Output: tracked objects with their 3D postures

[Avanzi et al. 2005] & [Zuniga et al. 2006]   [Boulay et al. 2006]

Video analysis: posture detection



Video analysis: ten 3D key human postures


A PRIORI KNOWLEDGE BASE
3D models of person and models of events
3D model of the scene
VIDEO ANALYSIS
EVENT RECOGNITION
MULTISENSOR EVENT FUSION
INPUT DATA
Video Sensors
Camera 1
Camera n
Person Detection
Person Tracking
Posture Detection
Video Event Recognition
Person Detection
Person Tracking
Posture Detection
Video Event Recognition
Multisensor Event Fusion
Activity Recognition
INPUT DATA
Environmental Sensors
SENSOR ANALYSIS
Sensor 1
Sensor m
Sensor Processing and Modeling
Sensor Processing and Modeling
Environmental Event Recognition
Environmental Event Recognition
Log-files (XML files)
Alarms
3D Visualization
OUTPUT DATA

Sensor analysis: method

Collecting information about interactions between people and the contextual objects.

Environmental sensors: binary sensors

- Give the status S for N physical objects
- Each sensor has two binary values: s = 0 and s = 1, representing "sensor Off" and "sensor On“ respectively
- Not always reliable sensors (e.g. wrong value)

Two probabilities are proposed to verify an occurred observation O for k sensors:

- P_d (probability of detection)

$$P(O_k = 1 | S_s = 1) = P_d$$

- P_f (probability of false alarm)

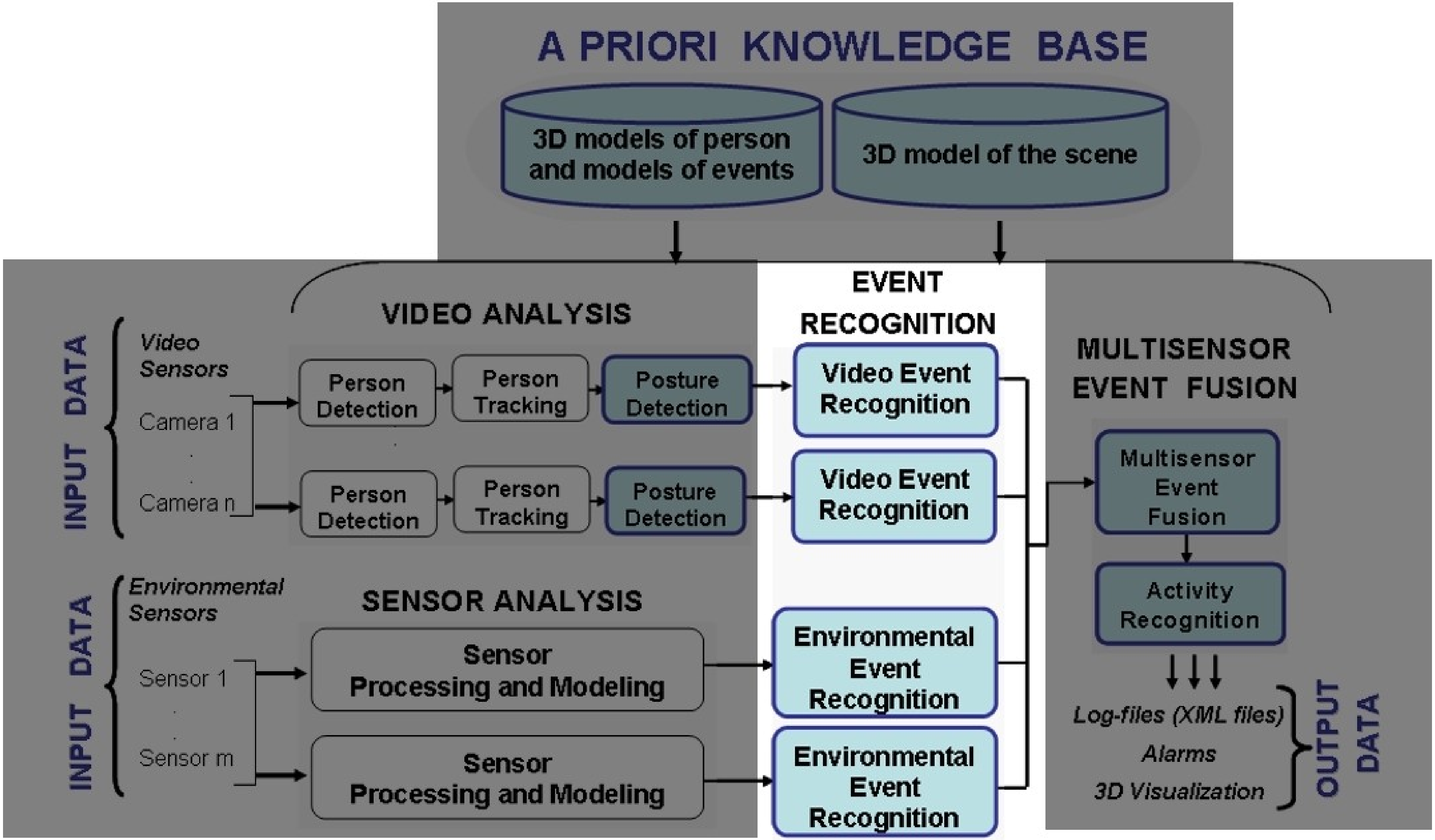
$$P(O_k = 1 | S_s = 0) = P_f$$

Sensor analysis: sensor model

Each sensor data is represented by

$$O = \langle Id; c; x; t; m; y; \Delta y \rangle$$

- Id: sensor identifier
- c: sensor class (e.g. contact, pressure)
- x: sensor location (3D position)
- t: time when the physical property is measured
- m: sensor mode (e.g. continuous, by event, on request)
- y: value of the physical property as measured by the sensor
- Δy: potential error in sensor observation (P_d, P_f)


A PRIORI KNOWLEDGE BASE
3D models of person and models of events
3D model of the scene
VIDEO ANALYSIS
EVENT RECOGNITION
MULTISENSOR EVENT FUSION
INPUT DATA
Video Sensors
Camera 1
Camera n
Person Detection
Person Tracking
Posture Detection
Video Event Recognition
Person Detection
Person Tracking
Posture Detection
Video Event Recognition
Multisensor Event Fusion
Activity Recognition
INPUT DATA
Environmental Sensors
SENSOR ANALYSIS
Sensor 1
Sensor m
Sensor Processing and Modeling
Environmental Event Recognition
Sensor Processing and Modeling
Environmental Event Recognition
Log-files (XML files)
Alarms
3D Visualization
OUTPUT DATA

Event recognition: event description language

Four types of event are defined:

- Primitive states: perceptual property of one or several physical objects
- Composite states: combination of primitive states
- Primitive events: change of primitive state values
- Composite events: combination of primitive/composite states and/or primitive/composite events

An event is mainly constituted of four parts:

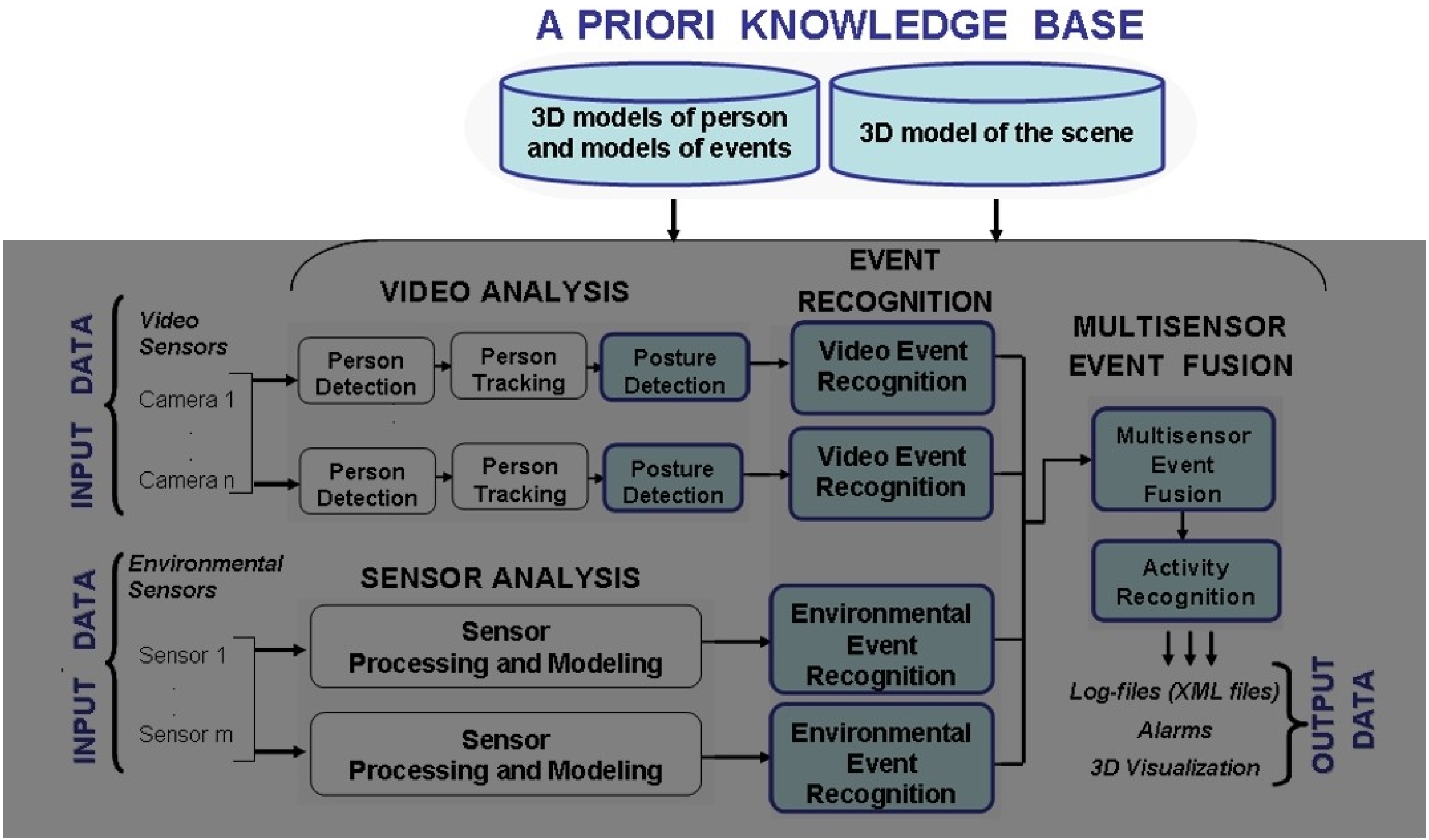
- *Physical objects:* all objects involved in an event E: i.e. mobile objects, contextual objects, zones of interest
- *Components:* list of states and sub-events involved in an event E
- *Constraints:* symbolic, logical, spatial and temporal relations between the physical objects and/or the components to be verified: e.g. before, after, duration, during, in, close to, ...
- *Alert:* a set of actions to be performed when an event E is recognized (Not-Urgent, Urgent and Very-Urgent).

Event recognition: event model

Syntax used to define an event model is:

EventType **(** event name,
    PhysicalObjects ((name of physical object: type of physical object))
    Components ((component 1)
                (component n))
    Constraints ((condition 1)
                (condition n))
    Alert (AText ("text alarm to display")
        AType ("type of the alarm"))
)

The event type can be a primitive state, a primitive event, a composite state, a composite event


A PRIORI KNOWLEDGE BASE
3D models of person and models of events
3D model of the scene
INPUT DATA
Video Sensors
Camera 1
Camera n
VIDEO ANALYSIS
Person Detection
Person Tracking
Posture Detection
Person Detection
Person Tracking
Posture Detection
EVENT RECOGNITION
Video Event Recognition
Video Event Recognition
MULTISENSOR EVENT FUSION
Multisensor Event Fusion
Activity Recognition
INPUT DATA
Environmental Sensors
Sensor 1
Sensor m
SENSOR ANALYSIS
Sensor Processing and Modeling
Sensor Processing and Modeling
Environmental Event Recognition
Environmental Event Recognition
Log-files (XML files)
Alarms
3D Visualization
OUTPUT DATA

Event recognition: new knowledge base of event models

For healthcare applications, I propose **100 event models** for daily activities:

- ✓ **58 customized video event models**, among them **26 posture-based events**, related to the human postures (e.g. standing) and transitions in human postures (e.g. standing up, sitting down, fainting, falling down)

- ✓ **26 new environmental event models** related to the data provided by the environmental sensors and to the status of each equipment in the scene

- ✓ **16 new multimodal event models** related to the complex activities at home, e.g. preparing meal, eating meal, using kitchen equipments

The proposed knowledge base is reusable in other homecare applications.

Event recognition: a priori knowledge

For homecare applications, I propose **a 3D model** of the scene:

- A 3D referential (calibration matrix and positions of video cameras)
- A 3D positions of environmental sensors
- Geometric areas to different rooms in the scene (e.g. kitchen, bedroom)
- Geometric zones of different zone of interest (e.g. cooking-zone, sleeping-zone)
- List of walls (e.g. kitchen right wall)
- List of different equipment (e.g. fridge, stove)

3D model of the person:

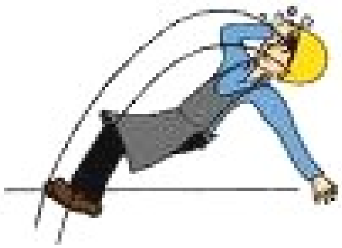
- 3D width
- 3D height
- 3D depth

Event recognition: video event models

Fainting event model

Two types of fainting situation:

- fainting without loss of balance
- fainting with loss of balance



PrimitiveEvent (*PersonFainting_without_Loss_Balance,*

PhysicalObjects ((*p* : Person))

Components ((c1: *PrimitiveState* Standing(p))

(c2: *PrimitiveState* Bending(p))

(c3: *PrimitiveState* SittingFlexedLegs(p))

(c4: *PrimitiveState* SittingOutstretchedLegs(p)))

Constraints ((c1; c2; c3; c4)

(c4 ***Duration*** >= threshold))

Alert (**AText** ("Person is Fainting ")

AType ("URGENT")))

- 1 physical object (person)
- 4 components (human postures)
- 2 constraints:
  - Sequential order
  - Duration of an event
- 1 **urgent** alert

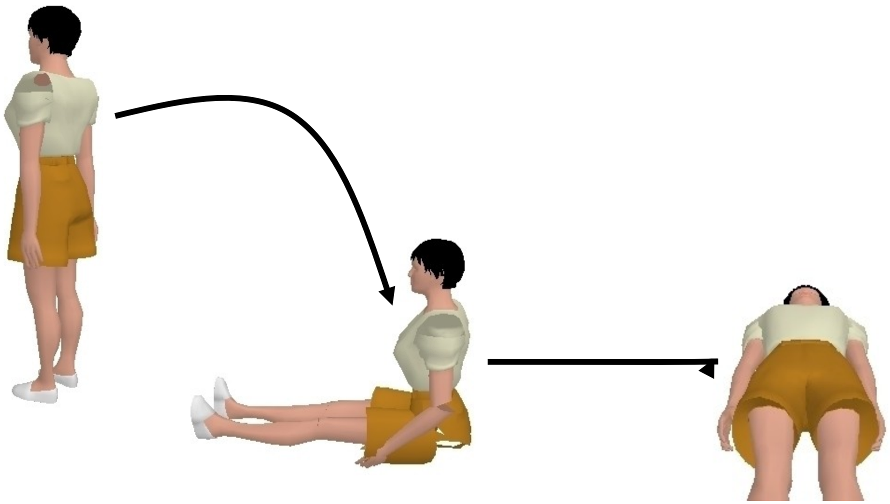
The threshold is calculated using 15 annotated fainting events

Event recognition: video event models

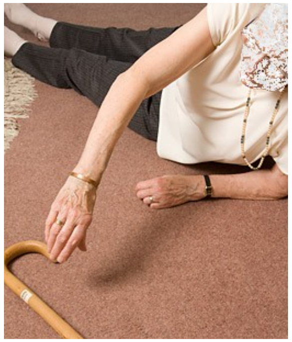
Falling down event model

Three models of falling down event:

- 1: Standing, sitting on the floor and lying on the floor with outstretched legs
- 2: Standing, bending and lying on the floor with outstretched legs
- 3: Standing, sitting on the floor and lying on the floor with flexed legs



Falling down 1



Event recognition: multimodal event models

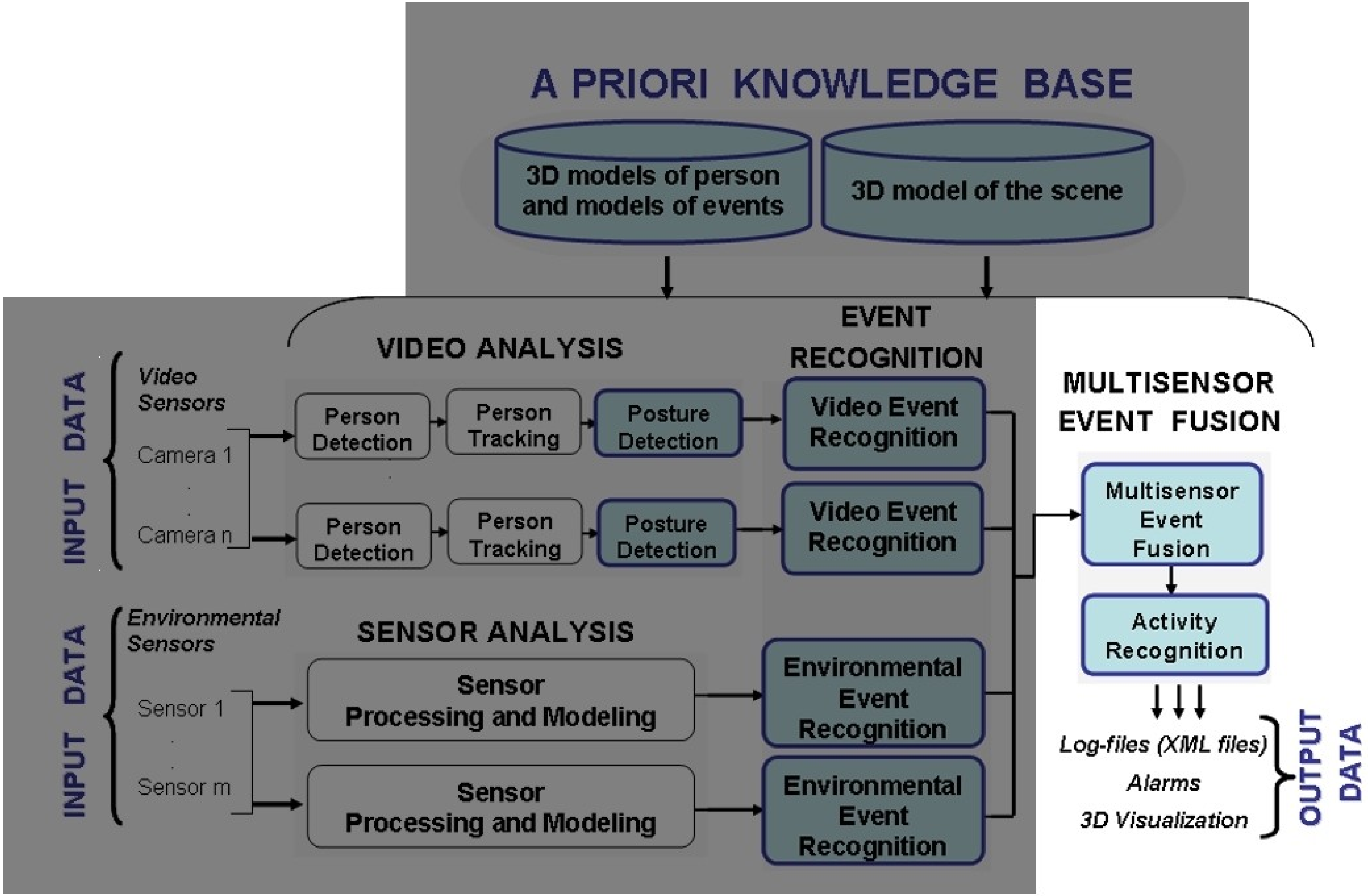
- 16 multimodal event models:

  Using fridge, cupboards, drawers, microwave, stove, telephone, watching TV, washing dishes, slumping in an armchair, eating meal, preparing breakfast, preparing lunch, preparing dinner, warming up meal, preparing cold meal, and preparing hot meal

Each event E is modeled with sub-events related to objects involved in the event E.

Example: “preparing lunch”

IF *a person is* ***located*** *close to the countertop in the kitchen for a long period* ***AND*** *(a person* ***accesses*** *to meal ingredients (e.g. fridge, cupboards)* ***AND*** *a person* ***accesses*** *plates or utensil cupboards)* ***AND*** *a person* ***uses*** *an appliance (e.g. microwave, stove) for a long period* ***THEN*** *a* ***meal is prepared****.*


A PRIORI KNOWLEDGE BASE
3D models of person and models of events
3D model of the scene
VIDEO ANALYSIS
EVENT RECOGNITION
MULTISENSOR EVENT FUSION
INPUT DATA
Video Sensors
Camera 1
Camera n
Person Detection
Person Tracking
Posture Detection
Video Event Recognition
Person Detection
Person Tracking
Posture Detection
Video Event Recognition
Multisensor Event Fusion
Activity Recognition
INPUT DATA
Environmental Sensors
Sensor 1
Sensor m
SENSOR ANALYSIS
Sensor Processing and Modeling
Environmental Event Recognition
Sensor Processing and Modeling
Environmental Event Recognition
Log-files (XML files)
Alarms
3D Visualization
OUTPUT DATA

Multisensor event fusion

Heterogeneous sensors: fusion at the event level

- **Input**: video and environmental events + a priori knowledge
- Event processed to synchronize them
- Synchronized events
- Understand which events are occurring

An event *E* is recognized at an instant *t*, if:

- all its components have been recognized,
- its last (using the temporal order) component being recognized at the given instant *t*

Multisensor event fusion: event synchronization

To cope with the different sensor measurement frequencies:

→ **synchronization**

Necessary for different sensors to have:

- The same temporal referential: timestamp synchronization
  - We define the measurement frequency $\boldsymbol{f_{sensor}}$: the number of times the sensor provides data to the multisensor fusion system per second
  - We define the measurement latency $T_{L,sensor}$: the measurement acquisition time and the measurement processing time (delay between sent data and the received data)
- The same spatial and semantic referential:
  - We propose a 3D model of the scene (geometric + sensors + semantic)

Multisensor event fusion: Dempster-Shafer

Dempster-Shafer Theory: generalization of traditional probability allows to better quantify uncertainty

Basic concepts for DST:

- Frame of discernment of sensors
  - e.g. two states of environmental sensors: Off and On

$$\Theta = \{0,1\}$$

- Mass function: distribution of belief

$$\mathcal{P}(\Theta) = 2^{\Theta} \rightarrow [0,1]$$

- Belief and plausibility: lower and upper bounds of probability

$$Bel(A) = \sum_{B \subseteq A} m(B) \qquad Pls(A) = \sum_{B \supseteq A} m(B)$$

- Uncertainty: $\delta(A) = Pls(A) - Bel(A)$

Multisensor event fusion: sensor uncertainty

Dempster-Shafer theory for evidential reasoning

- Handle sensor measurement errors

Example:

The person which drops his/her bag on the chair, may activate the chair sensor and give a false result

- How to detect if the person or the bag is on the chair (by using pressure sensors and video sensors)

Statistics of 20 video sequences of one human actor, show that pressure sensors work at 70%, and video sensor works at 75%

1- mass function

2- belief and plausibility

Multisensor event fusion: uncertainty of "sitting on chair"

Mass function for each sensor:

$$m_{VSChair}(\{Person\}) = 0.75 \qquad m_{VSChair}(\{\neg Person\}) = 0.25$$

$$m_{PSChair}(\{Person\}) = 0.70 \qquad m_{PSChair}(\{\neg Person\}) = 0.30$$

Summing up mass functions :

$$m_{PSChair,VSChair}(Person) = \frac{1}{2}\left(m_{PSChair}(Person) + m_{VSChair}(Person)\right)$$

$$= \frac{1}{2}(0.70 + 0.75) = 0.72$$

$$m_{PSChair,VSChair}(\neg Person) = \frac{1}{2}\left(m_{PSChair}(\neg Person) + m_{VSChair}(\neg Person)\right)$$

$$= \frac{1}{2}(0.30 + 0.25) = 0.27$$

Multisensor event fusion: uncertainty of “sitting on chair”

Belief (*Bel*) and Plausibility (*Pls*):

$$Bel(Person\_Sit\_Chair) = m_{PSChair,VSChair}(Person) = 0.72$$

$$Pls(Person\_Sit\_Chair) = m_{PSChair,VSChair}(Person) + m_{PSChair,VSChair}(\neg Person)$$
$$= 0.72 + 0.27 = 0.99$$

Calculate uncertainty:

$$\delta(Person\_Sit\_Chair) = Pls(Person\_Sit\_Chair) - Bel(Person\_Sit\_Chair)$$
$$= 0.99 - 0.72 = 0.27$$

- **A person is sitting on the chair with belief = 0.72**

Evaluation and results

Experimental site: Gerhome laboratory

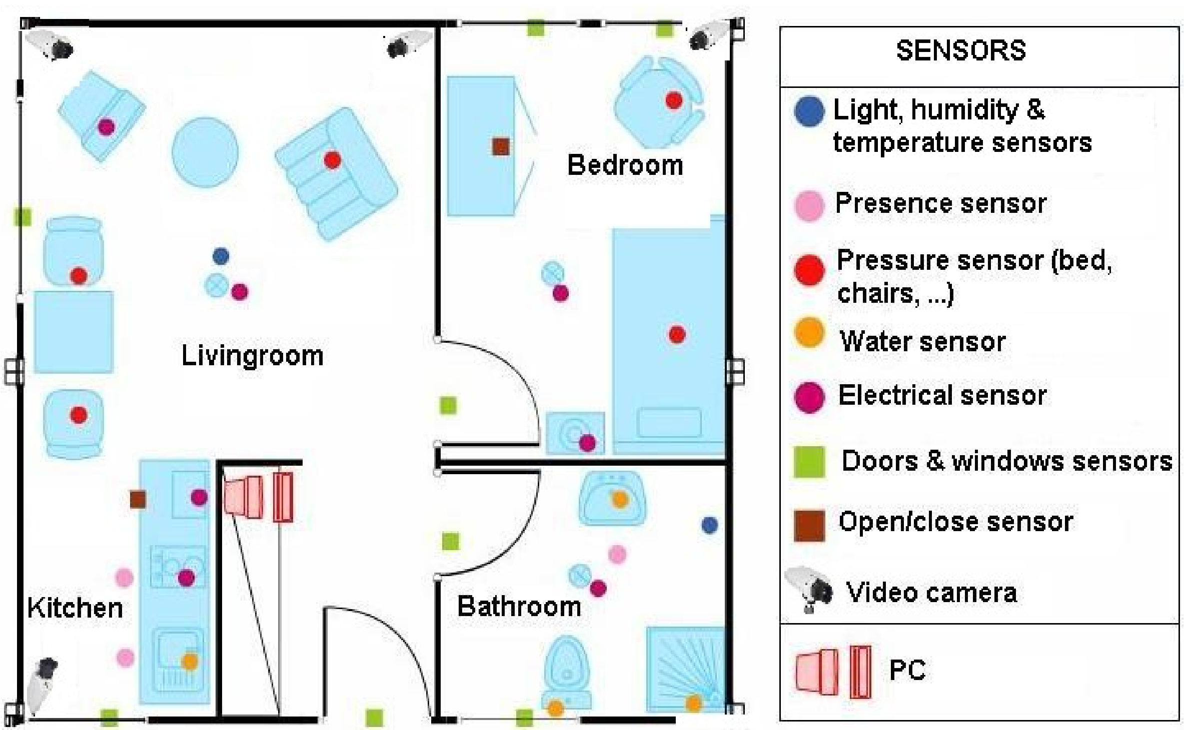
- GERHOME (Gerontology at Home) : homecare laboratory

http://www-sop.inria.fr/orion/personnel/Francois.Bremond/topicsText/gerhomeProject.html

- Experimental site in CSTB (Centre Scientifique et Technique du Bâtiment) at Sophia Antipolis http://gerhome.cstb.fr
- Partners: INRIA, CSTB, Nice Hospital, CG06…

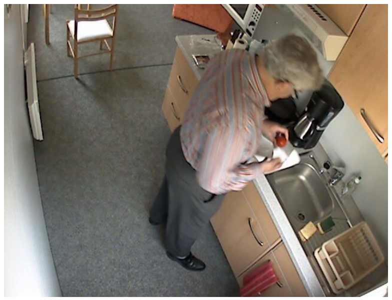
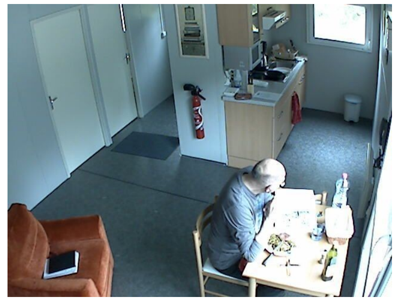
Evaluation and results: Gerhome laboratory

- Technical solutions to help the elderly people to stay at home
- Typical apartment of an elderly person living alone
- 41 m2 with entrance, bedroom, bathroom, livingroom, and kitchen

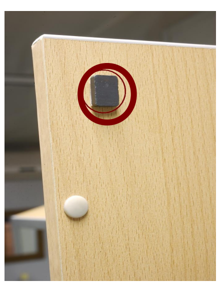
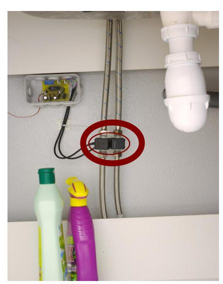


Evaluation and results: sensors in Gerhome laboratory

- **4 fixed video cameras** (1 in kitchen, 2 in livingroom, 1 in bedroom)

- **24** environmental sensors (**contact sensors** in cupboard doors, fridge doors and drawers; **water flow sensors** in water pipes in kitchen and bathroom; **electrical sensors** in outlets (stove, microwave, TV), **pressure sensors** under chairs, armchair and bed; & **presence sensors** near sink, stove and washbowl)

Evaluation and results: evaluation metrics

Classical metrics:

- **Precision P and sensitivity S**

  With TP: true positive, FP: false positive, FN: false negative

$$P = \frac{TP}{TP + FP} \qquad S = \frac{TP}{TP + FN}$$

- **F-score**

$$F = \frac{2P \times S}{P + S}$$

New specific metrics: comparison between 2 elderly people

- **Normalized Difference of Mean durations of Activity (NDA)**

  With m1 and m2 represent respectively mean durations of a certain activity of 2 people

$$NDA = \frac{|m1 - m2|}{m1 + m2}$$

- **Normalized Difference of Instance number (NDI)**

  With n1 and n2 represent respectively instance number of a certain activity of 2 people

$$NDI = \frac{|n1 - n2|}{n1 + n2}$$

Evaluation and results: 2 experiments

Experiment 1: with one human actor

- 15 video sequences at 10 fps
- Duration of each video sequence is about 20 minutes (about 9600 frames)
- 10 normal activities (e.g. using house equipment) and 2 abnormal activities (e.g. fainting and falling down) have been tested in Gerhome laboratory

Goal: test the **functionality** of the sensors and detect **abnormal activities** (alarming situations)

Experiment 2: with 14 elderly volunteers

In collaboration with Nice hospital and the CSTB, 14 elderly volunteers (i.e. 6 women and 8 men aged from 60 years to 85 years) were recruited and were asked to perform a set of household activities

- 56 video sequences at 10 fps (4 cameras x 14 volunteers)
- Duration of each video is about 4 hours and each video contains about 144 000 frames
- A set of daily activities (e.g. using kitchen equipment, preparing meal) has been tested in Gerhome laboratory
- Dataset of 9 elderly among the 14 elderly people have been analyzed (5 datasets with ground truth)

Goal: analyze behavioral profile and calculate the **degree of frailty** for each volunteer

Evaluation and results: video-based evaluation (experiment 1)

- Good recognition of a set of activities and human postures (video cameras)

States / Events	Ground truth	TP	FN	FP	Precision (%)	Sensitivity (%)	F- score (%)
In the kitchen	45	40	5	3	**93**	**88**	**90**
In the livingroom	35	32	3	5	**86**	**91**	**88**
Standing	120	95	25	20	**82**	**79**	**80**
Bending	92	66	26	30	68	70	69
Sitting	80	58	22	18	76	72	74
Slumping	35	25	10	15	**62**	71	66
Lying	6	4	2	2	66	66	66
Standing up	57	36	21	6	**85**	**63**	**72**
Sitting down	65	41	24	8	**83**	**63**	**71**
Sitting up	6	4	2	1	80	66	71

- Errors occur at the border between livingroom and kitchen
- Mixed postures such as bending and sitting due to segmentation errors

Evaluation and results: recognition of the "fainting" event

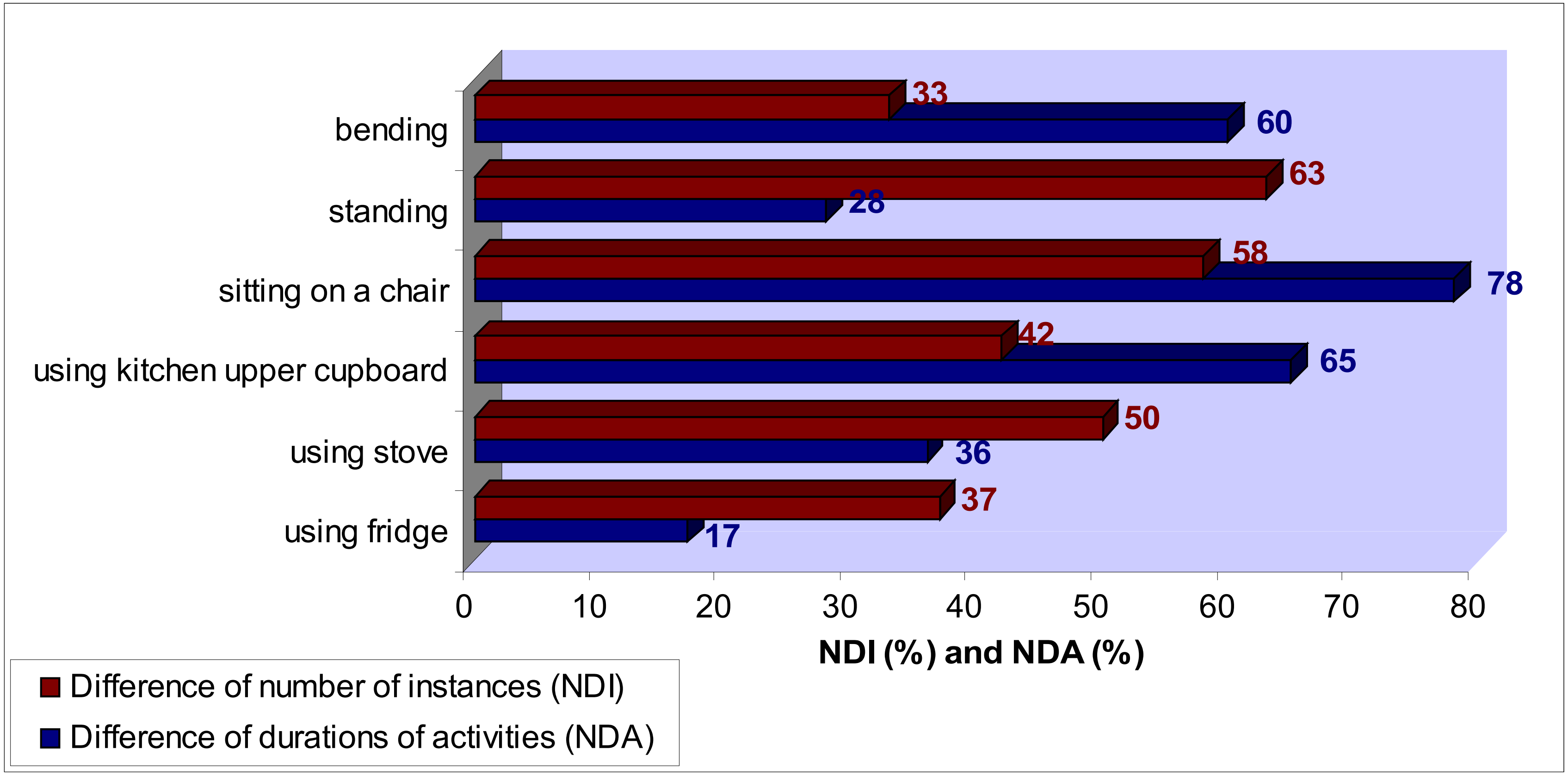
The person (human actor) is recognized with the postures "standing", "bending", "sitting on the floor with flexed legs", "sitting on the floor with outstretched legs".

Evaluation and results: recognition of the "falling-down" alarming situation

The person (human actor) is recognized with the postures "standing", " sitting on the floor with flexed legs ", and "lying on the floor with outstretched legs".

Evaluation and results: comparison between two elderly volunteers

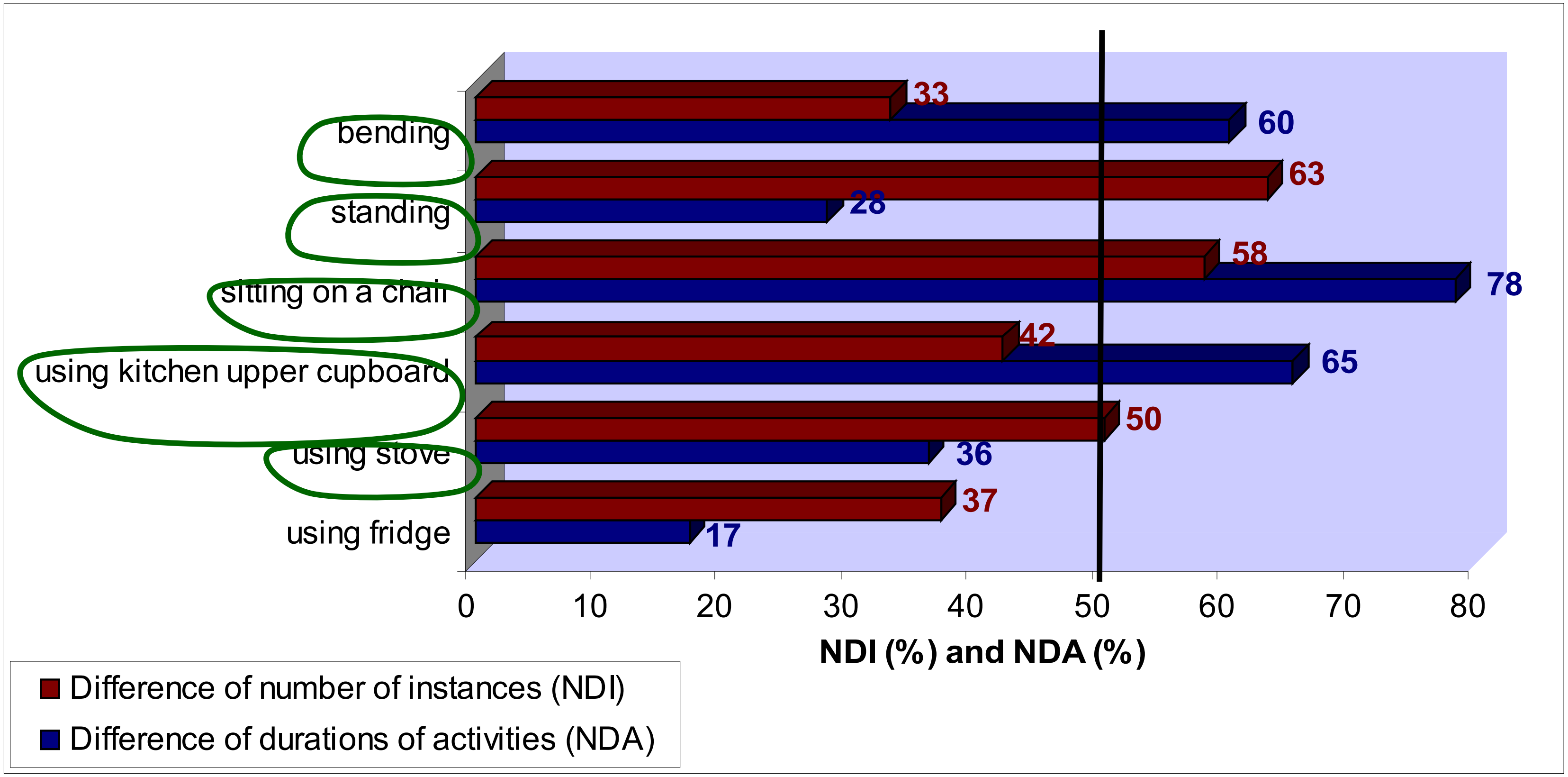
Volunteer 1: man of 64 years and volunteer 2: woman of 85 years



Big values = big difference in profile

Evaluation and results: comparison between two elderly volunteers

Volunteer 1: man of 64 years and volunteer 2: woman of 85 years

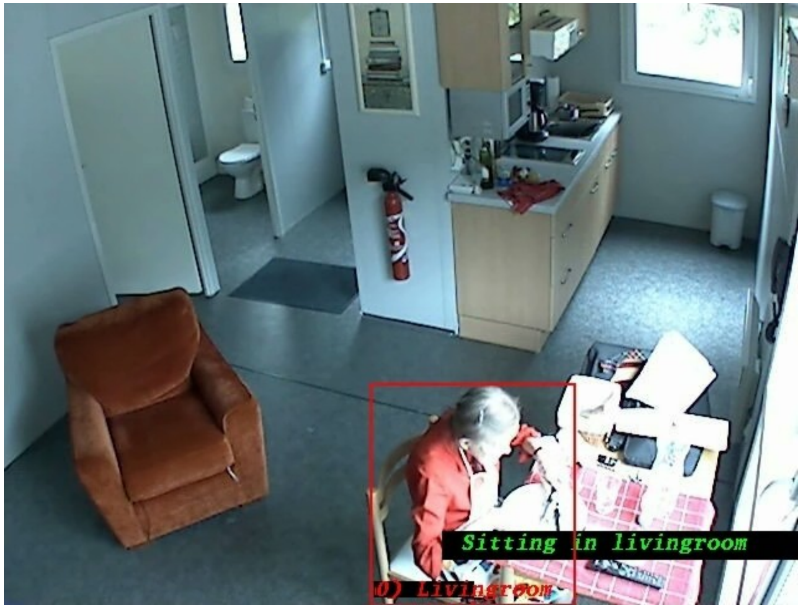


• **Different** profiles between the 2 volunteers

- **Greater ability** for the volunteer 1 to live in Gerhome laboratory

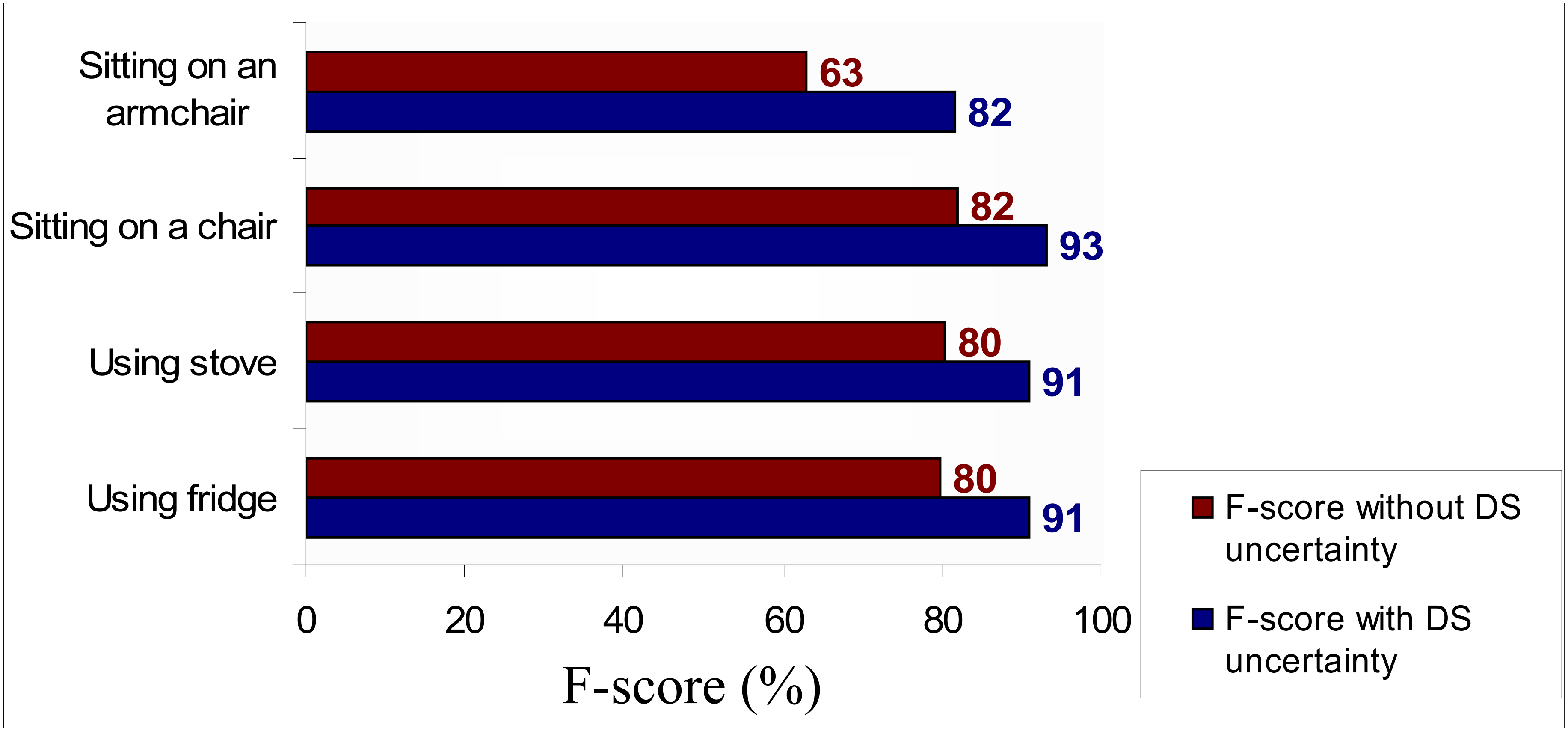
Evaluation and results: recognition of the "eating meal" activity

The elderly person is recognized "sitting on a chair in the livingroom" for a long time after preparing meal



Evaluation and results: Dempster-Shafer (DS), (experiment 2)

Using **DS uncertainty** shows some **improvements** in the recognition of activities (with about 20%)



Evaluation and results: leave-one-out cross validation

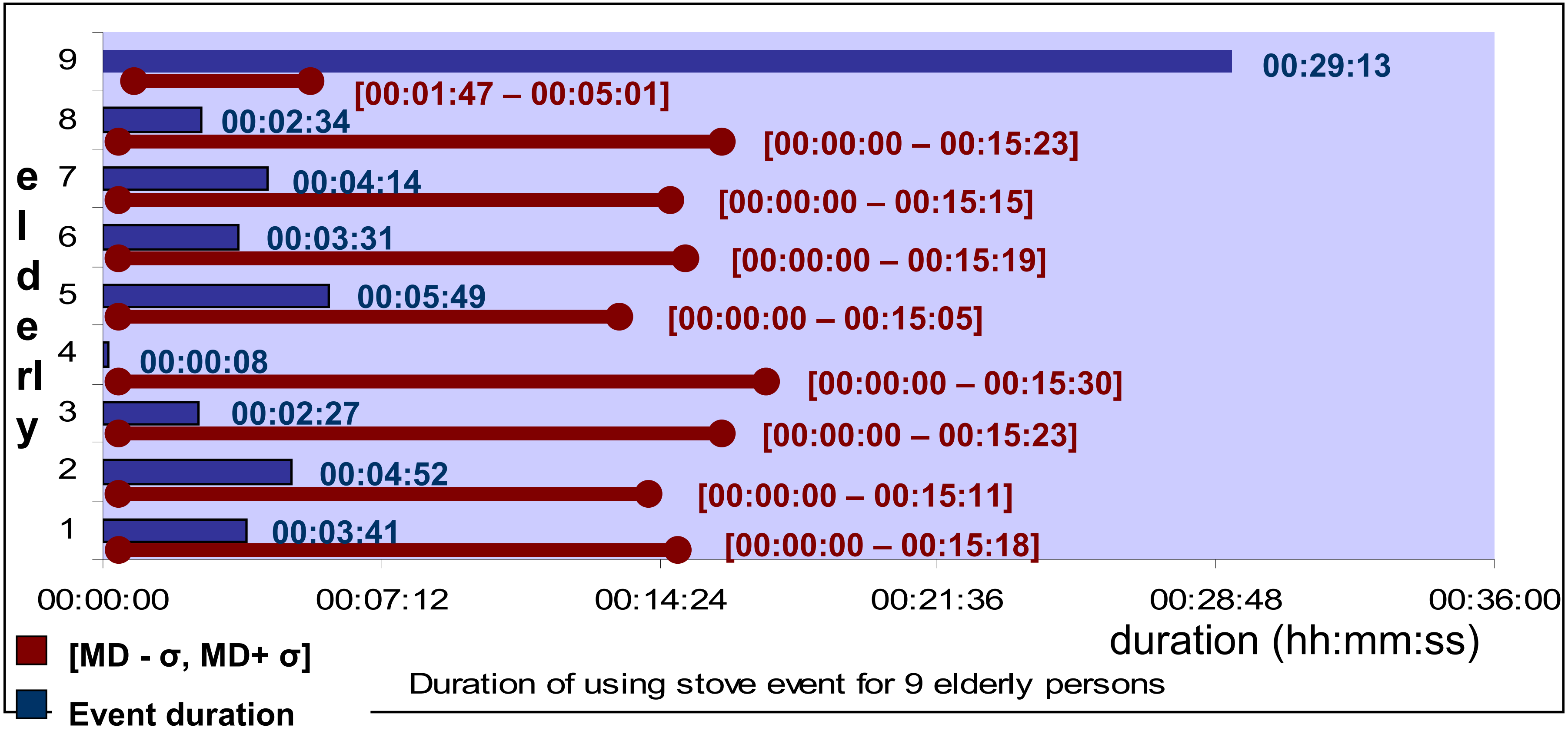
To bring out the **possible differences in the behaviors of the 9 volunteers**: compare behavioral profile of 9 elderly volunteers by using the **leave-one-out cross validation algorithm** on the activity duration

$$MD_{Ei,Pj} = \frac{\sum^{Pk \in P, Pk \neq Pj} d_{Ei,Pk}}{R}, \forall Pj \in P \qquad \sigma_{Ei,Pj} = \sqrt{\frac{1}{R}\sum_{K=1}^{R} d^2_{Ei,Pk} - MD^2_{Ei,Pj}}$$

- $\boldsymbol{MD_{Ei,Pj}}$: mean duration for an event Ei for each person without a person Pj;
- $\boldsymbol{d_{Ei,Pk}}$: duration for each event Ei for each person Pk;
- ***P*** = {P1; P2; P3; P4; P4; P5; P6; P7; P8; P9}
- ***R*** : represents the number of the training set of data (R=8)
- $\boldsymbol{\sigma_{Ei,Pj}}$: represents the standard deviation for each event Ei of each person without a person Pj;

Evaluation and results: behavioral profile (experiment 2)

Comparison between 9 elderly people (using stove event)

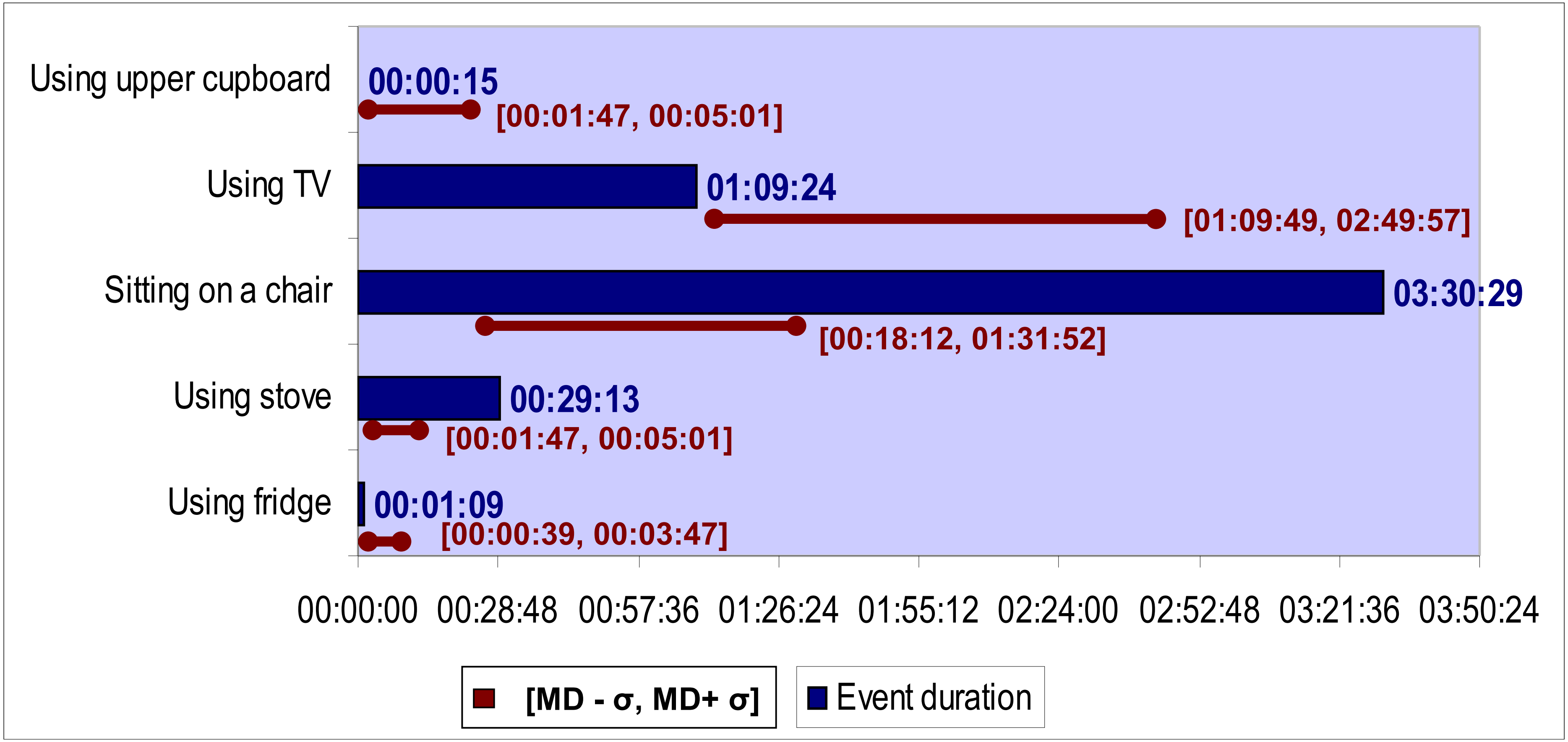


Duration of using stove event for 9 elderly persons

- Volunteer 9 (women of 85 years) has a fairly different profile from the others (e.g. some inabilities in using stove)

Evaluation and results: behavioral profile (experiment 2)

Comparison of 5 event durations between the volunteer 9 with the mean durations for the other 8 volunteers



Conclusion and future work

A new approach based on **multisensor analysis** by combining video events with environmental events to **recognize interesting activities at home**

✓Adapted to healthcare applications

The approach:

- Good results in the recognition of a set of daily activities at home
- Good results in detecting **alarming situations** (e.g. falling down)
- Allows us to calculate the **degree of frailty** of an elderly person
- About **changes in behaviors** for an elderly person, we need a lot of data during 6 months for an elderly person

Conclusion and future work (2)

Contributions

- A **knowledge base** of human activities is proposed: **100 events** have been modeled
  - 58 video events, 26 environmental events and 16 multimodal events
- An **extended constraint-based** approach for activity recognition
  - Non-video sensors
  - Multisensor fusion at the event level
  - Uncertainty in sensor measurements
- A **performance evaluation** of the approach has been done in a **real world** environment with **real elderly people**
- A **new dataset** (available on the web) of 14 elderly people performing a set of household activities has been proposed: **224 hours of video stream** (14 people x 4 hours x 4 cameras) and **14 log-files of environmental data**

Conclusion and future work (3)

Limitations

- **Sensors:** used environmental sensors give only **coarse information**
- not possible to **infer which food item is removed** from the fridge by simply considering the current state of the fridge door
- **Environment:**
- Gerhome laboratory **was not the volunteer real home**, volunteer behavior was **not completely natural**
- **Missing some activities** (e.g. activities taking place in the bathroom)

Future work

- **Learning event models:**
  - **Learn automatically** normal behavior models of everyday data
- **Extending the approach for several people living together:**
  - **Manage when several people** trigger the same set of sensors
  - **Extend the proposed knowledge base** of event models
- **Other environments:**
  - **In nursing homes** with healthy and frail elderly
  - **In hospital environment** with different patients with different diseases (e.g. Alzheimer)

List of the publications

International Journal:

- [1] **A computer system to monitor older adults at home: Preliminary results.** ZOUBA, N. and BREMOND, F. and THONNAT,M. and ANFOSSO, A. and PASCUAL, E. and MALLEA, P. and MAILLAND, V. and GUERIN, O. Gerontechnology Journal. July 2009, 8(3), pp 129-139.

World Congress:

- [2] **Assessing Computer Systems for the Real Time Monitoring of Elderly People Living at Home**. ZOUBA, N. and BREMOND, F. and THONNAT,M. and ANFOSSO, A. and PASCUAL, E. and MALLEA, P. and MAILLAND, V. and GUERIN, O. 19th IAGG World Congress of Gerontology and Geriatrics (IAGG 2009). July 2009.

International Conferences:

- [3] **Multisensor Fusion for Monitoring Elderly Activities at Home**. ZOUBA, N. and BREMOND, F. and THONNAT,M. IEEE International Conference on Advanced Video and Signal based Surveillance (AVSS 2009). September 2009.

- [4] **Monitoring Activities of Daily Living (ADLs) of Elderly Based on 3D Key Human Postures.** ZOUBA, N. and BOULAY, B. and BREMOND, F. and THONNAT,M. 4th International Cognitive Vision Workshop (ICVW 2008), pp 37-50. May 2008.

- [5] **Multisensor Analysis for Everyday Activity Monitoring.** ZOUBA, N. and BREMOND, F. and THONNAT,M. and VU, V.T. 4rth International Conference, Sciences of Electronic, Technologies of Information and Telecommunications (SETIT 2007). March 2007.

THANK YOU FOR YOUR ATTENTION