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Multi-sensors Analysis for Everyday Activity Monitoring

Nadia Zouba, Francois Bremond, Monique Thonnat, Van Thinh Vu

INRIA, Sophia-Antipolis Research Unit, Orion Project
2004 route des Lucioles B.P. 93,
06902 Sophia-Antipolis Cedex, France

Nadia.Zouba@sophia.inria.fr

Monique.Thonnat@sophia.inria.fr

Francois.Bremond@sophia.inria.fr

Van-Thin.Vu@sophia.inria.fr

Abstract: In this paper, we present a multimodal (video and contact sensors) monitoring approach for the automatic monitoring everyday activities of elderly people. The specificity of our approach consists in the integration of video analysis with other information resulting from contact sensors installed at home in order to improve the recognition of observed activities. After reviewing the state of the art, we describe the modeling of the scenarios of interest specified by medical experts. Then we present the multimodal event recognition process based on video and contact sensor analysis. Finally, we conclude by presenting preliminary results.

Keywords: event recognition, scene understanding, multimodal behavior analysis.

INTRODUCTION

In order to improve elderly life conditions at home and to reduce the costs of long hospitalizations, the medical world is more and more interested in telemonitoring techniques. These techniques will allow elderly people to stay safely at home, to benefit from an automated medical supervision and will delay their entrance in nursing homes. Thus, the objective of this work is the early detection of deteriorated health status and early diagnosis of illness. Our approach will consist in identifying a profile of a person - its usual and average behavior - and then to detect any deviation from this profile based on multi-sensor analysis and human activity recognition.

In this paper we propose a video monitoring framework fed by a network of cameras and contact sensors. The framework comprises 3 main tasks: (1) People detection, tracking and video event recognition; (2) Sensor stream filter and contact event recognition; (3) Multimodal event recognition.

The detection and tracking task detects and tracks mobile objects (mostly people) evolving in the scene. For each tracked mobile object the primitive event recognition task recognizes the events relative to the objects based on their visual features. Similarly, the contact event task recognizes the events characterized by contact information associated to the tracked objects. Finally the multimodal event recognition task consists in combining the previous video and contact events in order to recognize more complex events. These complex events are specified by medical experts thanks to a user friendly language.

Our main goal is to improve the techniques of automatic data interpretation using complementary sensors installed in the apartment such as video cameras, contact sensors installed on the doors, on the windows, in the kitchen cabinets and pressure sensors installed on the chairs. The proposed monitoring system takes, as described in figure 1, three types of input: (1) video stream(s) acquired by video camera(s), (2) data resulting from contact sensors embedded in the home infrastructure, and (3) a priori knowledge concerning event models and the 3D geometric and semantic information of the observed environment. The output of the system is the set of recognized events at each instant.

To attain our goal, we have used a video understanding platform described in [Avanzi & al. 2005], which includes an event recognition algorithm extended from [Vu & al. 2003]. After reviewing the state of the art, we give an overview of the proposed approach in section 2. Then we describe the video events (in section 3), the contact events (in section 4) and the multimodal events (in section 5). Finally, we conclude by presenting preliminary results on the homecare application.

1. State of the art

1.1. Health monitoring based on multi-sensor analysis

Automated health monitoring at home can be accomplished by (a) video monitoring cameras; (b) other sensors embedded in the home infrastructure and collecting behavioral and physiological data; or (c) a combination of both. However, in the literature, automated health monitoring is mostly based on passive non-video sensors to recognize simple activities. Passive monitoring has the inherent benefit of obviating the problems associated with incorrect use and subject compliance. For instance, Togawa has leaded one of the first projects using passive sensing for monitoring both physiologically and behaviorally everyday activities [Korhonen & al. 2003]. One of the pioneering research projects in telehealth was conducted at the University of New South Wales, Australia, aiming at exploring whether functional health status amongst the elderly could be accurately determined remotely by continuously monitoring relatively simple parameters that measured the interactions between participants and their environment [Celler & al. 1995]. The researchers reported a high level of acceptance by both the participants and their primary care providers, since the system was easy to use, effective, and potentially increased the efficiency of chronic disease management. In the United Kingdom, research and clinical trials examined the capabilities of intelligent monitoring systems to identify emergency situations based upon detected deviation from normal activity patterns. Out of the 61 alerts generated by the system, 46 were classified as false alerts and the other 15 as genuine, although no real emergencies occurred during the study [Sixthsmith. 2000]. Acceptance of the technology and its subsequent impact on the patient life quality were not evaluated.

Currently, research is being conducted at the Joseph-Fourrier University in France [Demongeot & al. 2002], [Virone & al. 2002], focusing on data fusion of multi-sensor information to generate health alarm conditions. The data analysis methods are tested using simulated physiological data. However, this approach has yet to be validated against clinically accepted standards in a clinical environment. Glascock and Kutzik [Glascock & al. 2000] have described a similar but non-intrusive system. During the proof of concept phase, this system was validated through Activities of Daily Living (ADL) in the suite of an urban hospital where a video camera and recorder captured the actual activities carried out by patients. An in-home testing phase was sequentially conducted in 1998 in several homes, with longer monitoring collected data representing 13 consecutive days [Barger & al. 1998], [Celler & al. 1996].

There have been several other research projects that have investigated the use of various sensor technologies for the monitoring of daily activities [Chan & al. 1995], [Dempster & al. 1997], [Fraley & al. 1998]. Data analysis techniques are based on statistical tools (including plots and histograms) to observe periodic patterns and infer activities [Fraley & al. 1998], comparing sensor data to a daily activity log [Dempster & al. 1997], and on neural networks to predict how long a person will spend time in or out of his/her single room environment [Goodman. 1999]. Other research efforts have examined the probability estimates to detect deviations from the normal amount of time a person spends in a room during an hour [Mathews & al. 1995].

Figure 1 illustrates the range of sensor technologies that are being investigated for activity monitoring. As shown there, researchers are exploring both environmental sensors and biosensors. The former class includes motion detectors that determine the location of the person, contact switches on cabinets and refrigerator doors that indicate whether they have been opened, pressure sensors that indicate whether a person is sitting in a bed or a chair, and thermometers that indicate whether a stove has been turned on. Biosensors are generally worn by a person to measure vital signs such as heart rate and body temperature. This range of sensors can be used to determine where a person is and what household objects he/she has used, as well as to get a general sense of his/her activity level. This information can be used to infer specific daily activities performed, and in turn, that knowledge, perhaps combined with biometric information, leads to a general assessment of health and wellbeing.

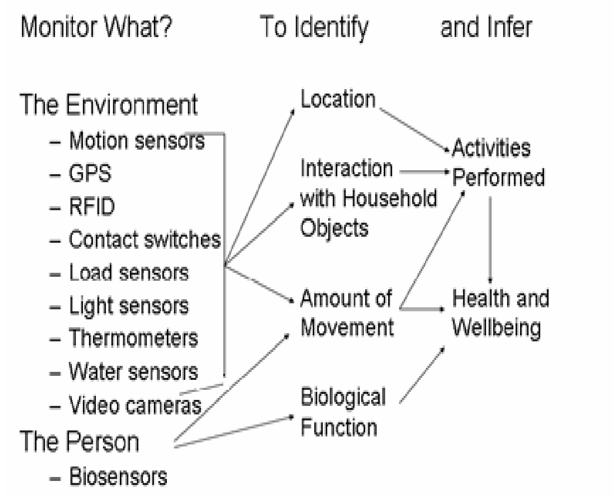


Figure 1: Sensors for activity monitoring

Most of these systems are able to compute the main trends of the observed activities, but few of them are able to analyze accurately people behaviors. To provide a more accurate analysis, we propose to take advantage of the work done in the video understanding domain.

1.2. Video understanding

In the recent past years, the automatic understanding of videos was applied to a large number of applications, for instance, monitoring of bank agencies, metro stations, road traffic, etc.

Many works were completed in the computer vision community in order to recognize normal and abnormal human activities [Avanzi & al. 2005]. There are several approaches which aim at recognizing temporal scenarios. We can summarize these approaches within two main categories based on (1) probabilistic/neural networks combining potentially recognized scenarios and (2) symbolic networks. For instance, [Howell & al. 2002] have proposed an approach to recognize a scenario based on a neural network (time delay Radial Basis Function), [Hongeng & al. 2000] have proposed a scenario recognition method that uses concurrence Bayesian threads to estimate the likelihood of potential scenarios. These probabilistic methods are useful, in the case of noisy images, to give an interpretation of the scene while taking into account the stochastic variations of the analysis.

In artificial intelligence, researchers usually use symbolic networks; their nodes correspond usually to the boolean recognition of scenarios. For example, [Rota & all. 2000] have used a declarative representation of scenarios defined as a set of spatio-temporal and logical constraints.

Another approach consists in using a symbolic network and to store partially recognized scenarios (to be recognized in the future). For instance, [Ghallab. 1996] has expressed a temporal scenario as a chronicle which is represented as a set of temporal constraints on time-stamped events. However, none of these understanding approaches have been applied to homecare monitoring and have used sensors such as contact sensors.

In this paper we propose an approach based on video and contact sensors to recognize everyday human activities. To our knowledge, this is the first monitoring system combining video and contact sensor analysis.

2. Proposed approach overview

Our approach consists in combining the video streams with the contact information to improve the recognition of elderly activities (Figure 2);

This approach has three main tasks:

- The first task consists for the vision component in detecting and tracking people and to recognize predefined video events. For instance, a typical video event is a person sitting down on a chair.
- The second task consists in acquiring sensor streams, in filtering them and in recognizing predefined contact events.
- Finally, the last task consists in combining the video and the contact events recognized by the previous tasks.

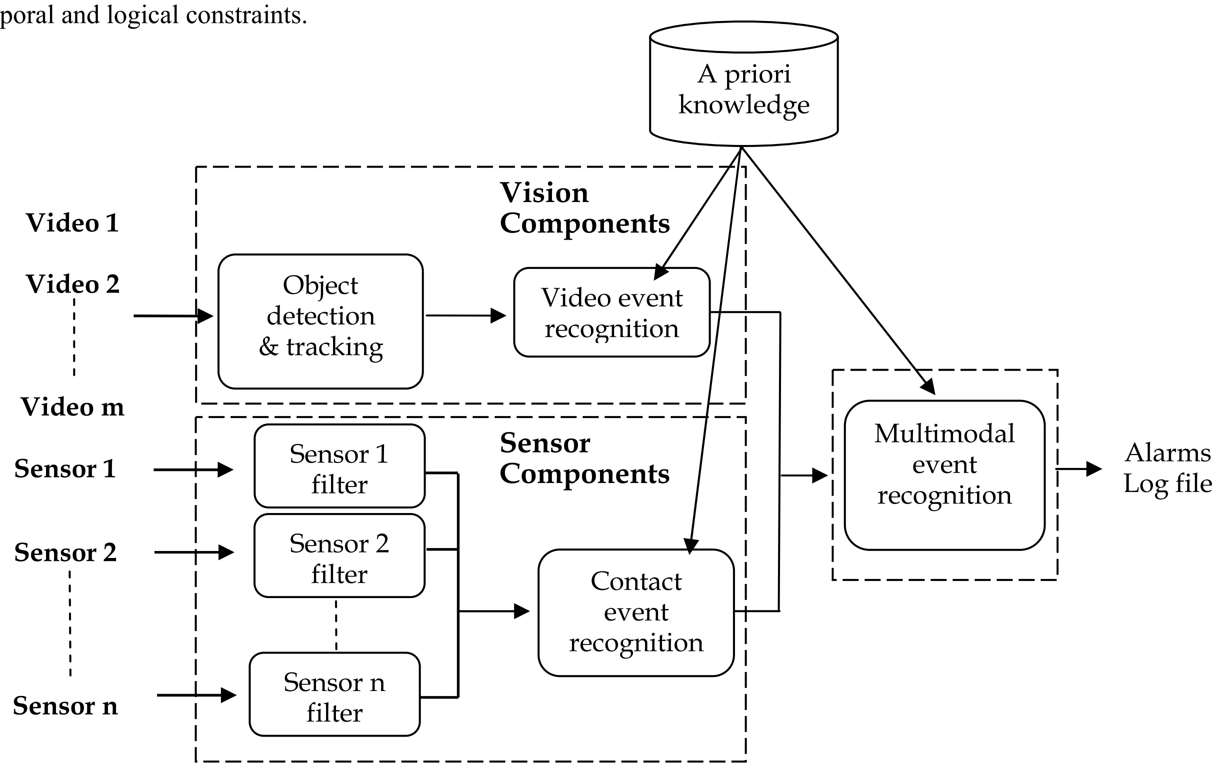


Figure 2: The architecture for the monitoring system is based on video and contact event recognition components

3. Video events

3.1. Detection & tracking person

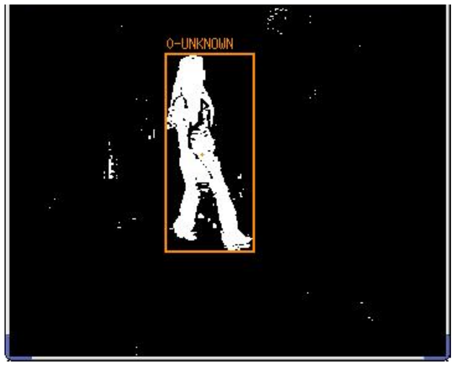
This task consists in detecting and tracking mobile objects within one camera. First, it consists in detecting for each frame the mobile objects in the scene and in classifying them with labels such as PERSON, corresponding to their type based on their 3D size and their shape,. A mobile object is described by 3D numerical parameters (center of gravity, position, height, width, length) and by a semantic class (PERSON, OCCLUDED PERSON, GROUP OF PERSONS, CROWD, NOISE or UNKNOWN).

The tracking task associates to each new mobile object an identifier and maintains it globally through out the whole video. Figure 3 illustrates the detection, classification and tracking of a person in the homecare laboratory.

3.2. Activity representation

The goal of event representation is to formalize the a priori knowledge for the scene understanding process. This knowledge corresponds to a 3D empty scene model of the observed environment and to a set of event models specified by medical experts. There are four types of perceptual activities: primitive states, composite states, primitive events and composite events. A state describes a stable situation in time characterizing one or several physical objects. A primitive state (e.g. a person is located inside a zone) corresponds to a perceptual property directly computed by the perceptual components (contact or vision). An event is an activity containing at least a change of state values between two consecutive times (e.g. a person enters a zone of interest (kitchen): he/she is outside the zone and then inside). A primitive event corresponds to a change of primitive state values and a composite event is a combination of states and/or events. An event is composed on five elements:

- ***"Physical objects"*** including mobile objects (e.g. individuals), equipments or zones of interest, etc.
- ***"Components"*** corresponding to the sub-events composing the event.
- ***"Forbidden components"*** corresponding to the events which should not occur during the main event.
- ***"Constraints"*** are conditions between the physical objects and/or the components (constraints can be temporal, spatial or logical).
- ***"Action"*** describes the actions to be taken when the event is recognized.



(a) Detection output

(b) Classification output

(c) Tracking output

Figure 3: Detection, classification and tracking of a person. On figure (a), the moving pixels are highlighted in white and clustered into a mobile object enclosed in an orange bounding box. On figure (b), the mobile object is classified as a person and a 3D parallelepiped matching the person indicates the position and orientation of the person. The figure (c) shows the individual identifier (IND 0) and a colored box associated to the tracked person.

An example of a primitive state is shown in figure 4. To describe the activities relative to elderly behaviors, the models of events of interest are specified by experts of the domain (e.g. medical experts). We have designed a declarative language to help with the definition of the events of interest based on a library of generic event models and an ontology detailed in [Bremond & all. 2004].

PrimitiveState ***(****Inside_zone,*
PhysicalObjects *((p : Person), (z : Zone))*
Constraints(*(p in z)****)***
Action (Priority "Normal"
Store_in_logfile))

Figure 4: Definition of the primitive state "Inside_zone"

3.3. Video event recognition

The video event recognition algorithm recognizes which events are occurring in a stream of tracked mobile objects. To recognize a primitive state, the algorithm performs a loop of two operations: (1) selection of a set of physical objects then (2) verification of the corresponding atemporal constraints until all combinations of physical objects have been checked. Once a set of physical objects satisfies all atemporal constraints, the primitive state is said to be recognized. The video event recognition algorithm is detailed in [Vu & all. 2003].

We illustrate on figure 5 the recognition of a primitive state "Inside_zone" in the homecare laboratory.

For this experiment, we have defined 2 primitive states/events: Inside_zone and Changes_zone.

Figure 5: Recognition of the primitive state "Inside_zone" in the homecare laboratory. A text message "Person is in the Livingroom" is displayed on the screen when the event is recognized.

4. Contact event detection

This section describes the contact event we have predefined in order to recognize the elderly activities specified by medical experts. A set of kitchen switches (14 sensors in total: 12 kitchen cabinet drawer switches, one on the microwave oven door and one on the refrigerator door), were installed in the homecare laboratory to monitor the everyday elderly activities.

The contact sensors provide a set of four attributes: the timestamp, the identifier (Id) of the sensor, the sensor status ('O' (open) or 'C' (closed)) and the duration indicating how long the equipment has been opened.

The kitchen switches are on-off sensors which reflect the status of the associated drawer or door. They are grouped by four units on the same module of transmission, (for example, the transmitter with the address 106 is connected to the second sensor with the id 106-1).

Each detection is recorded with its date and time of occurrence. Information is stored in a XML file and transmitted to the scene monitoring system. This file is read by the acquisition contact component, where data are stored in a temporary table of contact information with the following format:

[Date]-[Hour] [Sensor Id] [Status] [Duration]

with:

Date[Year][Month][Day]

Hour[HH][MM][SS].[sss]

Sensor Id ϵ [106-0, 106-1, 106-2]

Status ϵ ['O', 'C']

Duration [SS.sss]

From this information, we infer the corresponding contact event. For instance, we have defined the event describing the four states corresponding to the opening and closing of the kitchen cupboards, Upper Cupboard is the dishes cupboard, LowerCupboard is the food cupboard:

- ***PrimitiveState*** ***(****UpperCupboard_closed,*
  PhysicalObjects *((c: Equipment))*
  Constraints *((IsUpperCupboardClosed(c)))* ***)***
- ***PrimitiveState*** ***(****UpperCupboard_open,*
  PhysicalObjects *((c : Equipment))*
  Constraints*((IsUpperCupboardOpen(c)))* ***)***
- ***PrimitiveState*** ***(****LowerCupboard_closed,*
  PhysicalObjects *((c: Equipment))*
  Constraints *((IsLowerCupboardClosed(c)))* ***)***
- ***PrimitiveState*** ***(****LowerCupboard_open,*
  PhysicalObjects *((c : Equipment))*
  Constraints*((IsLowerCupboardOpen(c)))* ***)***

For this experiment, we have defined 10 primitive states/events:

Refrigerator_Open,
Refrigerator_Closed,
UpperCupboard_Closed,
UpperCupboard_Open,
LowerCupboard_Closed,
LowerCupboard_Open,
PersonClose_UpperCupboard,
PersonOpen_UpperCupboard,
PersonClose_LowerCupboard,
PersonOpen_LowerCupboard,

5. Multimodal composite event recognition

Using multiple sensors in monitoring system can reduce the detection errors and improve people tracking. Multisensor information fusion, is a relatively new engineering discipline used to combine information from multiple and diverse sensors and sources in order to perform inferences about events, activities and situations.

The video and contact event recognition aims at recognizing complex temporal events that combine both video and contact events. Those events are predefined in the knowledge base and correspond to the terminal events of the application.

To model the activities of interest specified by medical experts, we have defined 3 composite events: Using_food, Using_dishes, Prepare_meal. As an example, we describe the meal preparation event model. Meal preparation entails at least motion in the kitchen and use of cabinets where food, plates and/ or utensils are stored. Depending on the type of meal it may involve the use of appliances, such as stove, oven, or microwave oven. A definition for meal preparation is:

IF the resident is in the kitchen **AND** ((resident accesses food cabinet **AND** resident accesses dishes cabinet) **OR** resident uses an appliance) **THEN** a meal is prepared

Presence in the kitchen can be indicated by motion (video camera) in the kitchen lasting for a minimum period of time, whereas the use of meal ingredients can be indicated by the use of a food storage cupboard or the refrigerator (contact sensors), etc.

We present in first, the definition of four primitive events,

personOpen_UpperCupboard,
personClose_UpperCupboard,
personOpen_LowerCupboard,
PersonClose_LowerCupboard

- ***PrimitiveEvent(****personClose_UpperCupboard****,***
  PhysicalObjects(*(p: Person), (c : Equipment)****)***
  Components(
  (uc_close:*PrimitiveState UpperCupboard_closed(c)****))***
  (p_far: *PrimitiveState far_from(p, c)****)***
  Constraints(*(uc_close* ***before_meet*** *p_far)* ***)***

- ***PrimitiveEvent(****personOpen_UpperCupboard****,***
  PhysicalObjects(*(p: Person), (c : Equipment)****)***
  Components(
  (p_close: *PrimitiveState Close_to(p, c)****)***
  (uc_open:*PrimitiveState UpperCupboard_open(c)****))***
  Constraints(*(p_close* ***before_meet*** *uc_open)* ***)***

- ***PrimitiveEvent(****personOpen_LowerCupboard****,***
  PhysicalObjects(*(p: Person), (c : Equipment)****)***
  Components(
  (p_close: *PrimitiveState Close_to(p, c)****)***
  (lc_open: *PrimitiveState LowerCupboard_open(c)****))***
  Constraints(*(p_close* ***before_meet*** *lc_open)* ***)***

- ***PrimitiveEvent(****personClose_LowerCupboard****,***
  PhysicalObjects(*(p: Person), (c : Equipment)****)***
  Components(
  (lc_close: *PrimitiveState LowerCupboard_closed(c)****))***
  (p_far: *PrimitiveState far_from(p, c)****)***
  Constraints(*(lc_close* ***before_meet*** *p_far)* ***)***

In the illustration below, we present a model of the Using_food, Using_dishes and prepare meal events:

- ***CompositeEvent(****Using_food,*
  PhysicalObjects(*(p: Person), (LowerCupboard: Equipment), (Kitchen: Zone))*
  Components(*(p_inz: PrimitiveState inside_zone (p, Kitchen))*
  (p_open_lc: PrimitiveEvent personOpen_LowerCupboard(p, LowerCupboard))
  (p_close_lc: PrimitiveEvent personClose_LowerCupboard(p, LowerCupboard)))
  Constraints(*(p_inz before_meet p_open_lc)*
  (p_open_lc Duration > 10)
  (p_open_lc before_meet p_close_lc) ***))***

- ***CompositeEvent(****Using_dishes,*
  PhysicalObjects*((p: Person), (UpperCupboard: Equipment), (Kitchen: Zone))*
  Components*((p_inz: PrimitiveState inside_zone (p, Kitchen))*
  (p_open_uc: PrimitiveEvent personOpen_UpperCupboard(p, UpperCupboard))
  (p_close_uc: PrimitiveEvent personClose_UpperCupboard(p, UpperCupboard)))
  Constraints*((p_inz before_meet p_open_uc)*
  (p_open_uc Duration > 10)
  (p_open_uc before_meet p_close_uc)))

- ***CompositeEvent (****Prepare_meal****,***
  PhysicalObjects *((p: Person), (eq: Equipment))*
  Components*(*
  (p_food: ***CompositeEvent*** *Using_food (p, eq))*
  *(p_dishes:****CompositeEvent*** *Using_dishes (p, eq)))*
  Constraints *((p_food; p_dishes))*
  Action *(Priority "Normal", Text "the person prepares a meal"))*

The multimodal (contact-video) event recognition algorithm recognizes which events are occurred using primitive video events detected by the video detection module [section 3] and the contact events detected by the contact detection module [section 4].

The event models contain the list of physical objects involved in the primitive event. To recognize an event composed of two (or one) sub-events, the recognition algorithm selects a set of physical objects matching the remaining physical object variables of the event model.

The algorithm then looks back in the past for any previously recognized state/event that matches the first component of the event model. If these two recognized components verify the event model constraints, the event is said to be recognized. In order to improve time processing of the complex event recognition process, after each recognized event, the system focuses on all composite event models, the last component of which corresponds to this recognized event. Then the recognition of complex events is performed in a similar way to the recognition of events composed of two sub-events. The activity recognition algorithm is based on the method of Vu and all [Vu & all. 2003].

6. Results & evaluation

To validate our work, we have tested a set of scenario on homecare laboratory. This section describes and discusses the experimental results. First, we describe the laboratory. Second, we show early results. Finally, we discuss our proposed method and its performances.

6.1. Presentation of the homecare project

The laboratory we used for experiments is a 40m² apartment which is composed of a bedroom, a bathroom and a living-room including a kitchen (figure 6). The video sensors (4 video cameras) are installed in each room of the apartment in order to establish where the person is located at any moment. A set of contact sensors are installed in the laboratory (14 sensors in total: 6 kitchen cabinet drawer switches, 6 doors and windows, one on the microwave oven door and one on the refrigerator door), which provide information about elderly activities, such as "prepare a meal", and so on. These sensors communicate with the system by radio waves.

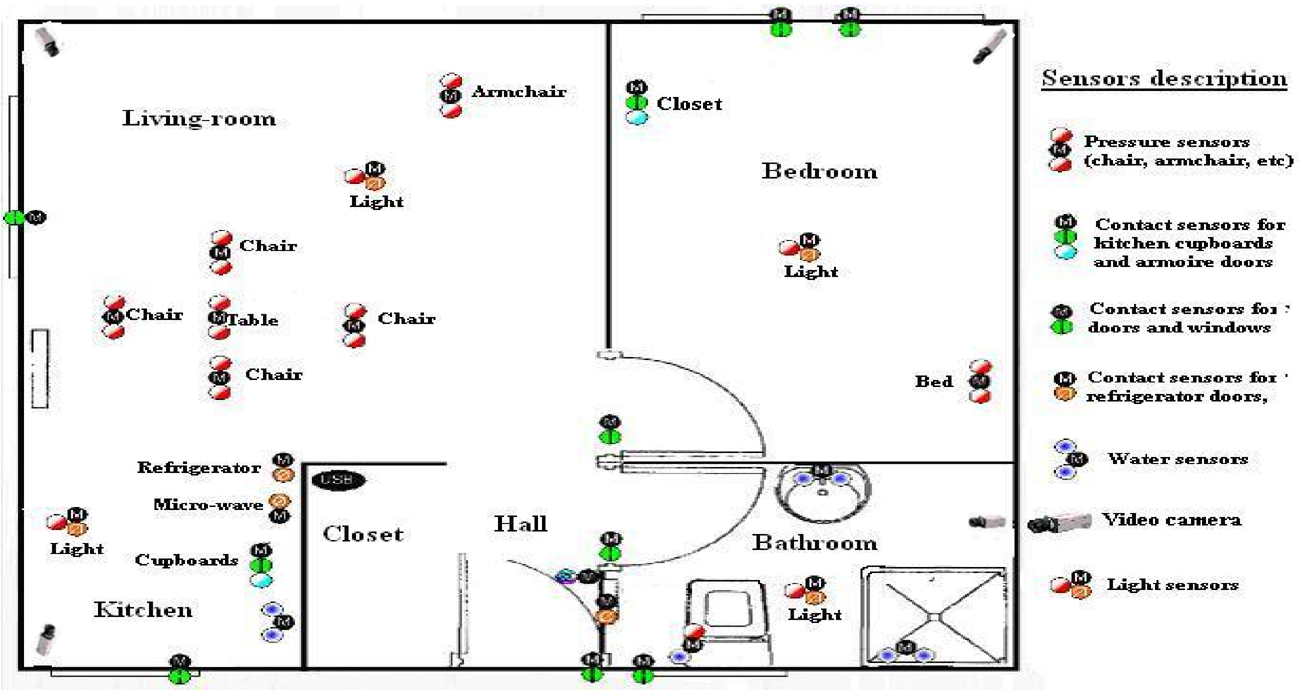


Figure 6: Position of the sensors inside the apartment

6.2. Multimodal event recognition results

In this section we present preliminary results of the multimodal (video and contact) event recognition process.

When the system recognizes correctly that an activity has occurred, we score a true positive (TP); an incorrect recognition is scored as a false positive (FP). If an activity occurs and the system does not report it, we score a false negative (FN). Table 1 shows the recognition results for the specified elderly activities. We use two standard metrics: the precision (1) and the sensitivity (2). The precision is the ratio between the numbers of true positives (correct recognition) and the sum of the numbers of true and false positives (corresponding to all events to be recognized). The sensitivity is the ratio between the number of true positives and the sum of the numbers of false negatives and true positives (corresponding to all detected events).

These results are describes on table 1

$$\mathrm{Pr}ecision = \frac{TP}{TP + FP} \tag{1}$$

$$Sensitivity = \frac{TP}{FN + TP} \tag{2}$$

Activity	*TP (%)*	*FP (%)*	*FN (%)*	*Precision*	*Sensitivity*
Inside zone	***100***	***0***	***0***	***1***	***1***
Open cupboard	***98***	***0***	***2***	***1***	***0,98***
Close cupboard	***98***	***0***	***2***	***1***	***0,98***
Using food	***94***	***4***	***2***	***0,959***	***0,979***
Using dishes	***94***	***4***	***2***	***0,959***	***0,979***

Table 1: video-contact recognition results

The primitive state (Inside zone) has been well recognized from video sensors and the primitive events (Open /close cupboard) are correctly recognized from contact sensors. These primitive events define the “using food” and “using dishes” composite events, which defined the “prepare meal” model. This model is only using the cupboard sensors. The other sensors (such as the microwave oven door and the refrigerator door sensors) are not activated. These preliminary results are encouraging to recognize more composite events using multi-sensors for the homecare applications.

7. Conclusion

Interest in intelligent assistance technology for elderly people is growing rapidly. This paper has described a contact-video monitoring platform able to automatically recognize the specified elderly activities using both contact and video information for an apartment equipped with contact and video sensors. The first results enable us to show that a person can be precisely located in the room (kitchen, living room, etc). These results show also that combining information from contact sensors with the one from video sensors improve significantly the recognition of elderly activities both in terms of quality and robustness.

In the future we will use this recognition of everyday activities to compute on a long term period (one month) the behavior profile of the observed person and we will detect any pathologic evolution of this profile.

Other high-priority objectives consist in modeling other activities including falls, eating habits, and so on to validate our approach.

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