A Multi-Sensor Approach for Activity Recognition in Older Patients

Carlos Fernando Crispim Junior[1], Francois Bremond[1,2]
[1]Institut de Recherche en Informatique et en Automatique
[2]EA CoBTeK Université de Nice Sophia Antipolis
Sophia Antipolis, France
{carlos-fernando.crispim_junior,francois.bremond}@inria.fr

Veronique Joumier[2,3]
[3]Centre Mémoire de Ressources et de Recherche de Nice
Nice, France
veronique.joumier@inria.fr

***Abstract* — Existing surveillance systems for older people activity analysis are focused on video and sensors analysis (*e.g.*, accelerometers, pressure, infrared) applied for frailty assessment, fall detection, and the automatic identification of self-maintenance activities (*e.g.*, dressing, self-feeding) at home. This paper proposes a multi-sensor surveillance system (accelerometers and video-camera) for the automatic detection of instrumental activities of daily living (IADL, *e.g.*, preparing coffee, making a phone call) in a lab-based clinical protocol. IADLs refer to more complex activities than self-maintenance which decline in performance has been highlighted as an indicator of early symptoms of dementia. Ambient video analysis is used to describe older people activity in the scene, and an accelerometer wearable device is used to complement visual information in body posture identification (e.g., standing, sitting). A generic constraint-based ontology language is used to model IADL events using sensors reading and semantic information of the scene (*e.g.*, presence in goal-oriented zones of the environment, temporal relationship of events, estimated postures). The proposed surveillance system is tested with 9 participants (healthy: 4, MCI: 5) in an observation room equipped with home appliances at the Memory Center of Nice Hospital. Experiments are recorded using a 2D video camera (8 fps) and an accelerometer device (MotionPod®). The multi-sensor approach presents an average sensitivity of 93.51% and an average precision of 63.61%, while the vision-based approach has a sensitivity of 77.23%, and a precision of 57.65%. The results show an improvement of the multi-sensor approach over the vision-based at IADL detection. Future work will focus on system use to evaluate the differences between the activity profile of healthy participants and early to mild stage Alzheimer's patients.**

Keywords – Event Streams Fusion; Instrumental Activities of Daily Living; Dementia; Elderly

I. INTRODUCTION

The growth of older people population in past years has highlighted the importance of the development of tools that could extend their independent living, and to improve the diagnosis and treatment of age-related diseases. Information and Communication Technologies (ICT) have proposed wearable sensors [1-2], smart homes, and video surveillance systems [3-7] to address older people surveillance, detect emerging patterns of frailty and falling down events, and to support the early diagnosis of aging related diseases (*e.g.*, Alzheimer, Parkinson, Mild Cognitive Impairment - MCI). People surveillance is generally based in smart home approaches, which analyzes older people daily living activities using a set of heterogeneous sensors placed at home appliances (*e.g.*, infrared presence sensors, contact sensors, temperature sensors, microphones, and video cameras). Their goal is generally to identify falling down events or emerging patterns of frailty by the detection and analysis of a set of self-maintenance activities known as Activities of Daily Living (ADL[8], *e.g.*, hygiene, toilet use, eating, resting, and dressing) [10-12]. Although a multi-sensor approach enriches the quantity of data about the person daily routine, the multiple sources of readings also increase the complexity of data analysis process, as it is necessary to choose the relevant sensor to detect the activity of interest (disregarding the existent data storage issues).

Video-monitoring systems are an alternative to the fully sensor equipped smart-homes, as they can replace or be used in parallel to reduce the number of sensors necessary to describe the overall activity of a person. Existing applications vary from fall detection to ADL detection at constrained environments [3-7]. An ontology-based approach was shown for modeling the context of human status (*e.g.*, body posture) and the environment context (semantic information about the scene). The models use information provided by a set of cameras for person detection, and accelerometer devices attached to objects of daily living for environment events triggering (*e.g.*, TV remote control or doors use). A rule-based reasoning engine is used for processing and combining both models types at activity detection level. The ontology tries to solve the semantic gap among the human activities (and scene context) and the sensors raw signals [28]. A Fuzzy logic scheme [27] was also proposed to cope with multiple sensor fusion at activity analysis in a smart home. Audio, infrared sensors and a wearable device (acquiring physiological signals, like, ECG, and body posture) are combined to infer ADLs events.

Although daily activity surveillance can support the analysis of medium- to long-term patterns of activity, in-lab clinical protocols supported by ICT have been recently proposed to analyze a person performance in specific activities (like ADL), that could highlight emerging symptoms of a certain diseases. For example, wearable devices have been used to assess older people motor functions performance in a gait analysis test. Patients wear a chest or fist sensor which automatically extracts parameters about their gait performance (e.g., stride length and cadence, vital signals). These parameters are used to identify disturbances in gait patterns that could be associated to emerging symptoms of Dementia (*e.g.*, Alzheimer, MCI, and Parkinson) [16-18, 22].

This paper proposes a multi-sensor surveillance system using heterogeneous sensors data (video and accelerometer recordings) to identify activities during a medical clinical protocol. An ontology approach is used to model the semantic information about activities and the clinical protocol tasks. Accelerometer data is combined with visual information to identify the body posture of the person in situations where video camera data is not sufficient due to occlusion or scene characteristics that affect people detection on the scene.

The set of activities analyzed differ from previous studies as Instrumental Activities of Daily living (IADL) are used instead of ADL. IADL set of activities have been recently discussed as a better estimator for the evaluation of emerging neuropsychiatric symptoms, as they are associated with tasks that require independence, organization, judgment and sequencing abilities (*e.g.*, using the phone, shopping groceries, organizing medications, and managing personal finances) [8].

The system prototype is tested in an ongoing medical clinical protocol under development by the Memory Center of Nice Hospital, which intends to quantitatively and objectively assess older people executive functions and functional abilities. The long-term goal of this approach and the clinical protocol is to differentiate early stage Alzheimer's patients from healthy participants.

The main contributions of the present work are the use of accelerometer-based and visual-based information for posture recognition. The sensors data are combined using an ontology language similarly to [28], but the set of sensors used is different. The IADLs recognition instead of ADLs as previous works discussed is stated as a contribution for the clinical domain. Next sections will present the proposed multi-sensor approach, the clinical protocol where the proposed system is tested, and the preliminary results.

II. Materials and Methods

A. Clinical Protocol

Participants aged more than 65 years are recruited by the Memory Center (MC) of the Nice Hospital. Inclusion criteria of the AD group are: diagnosis of AD according to NINCDS-ADRDA criteria and a Mini-Mental State Exam (MMSE) [19, 23] score above 15. AD participants which have significant motor disturbances (per the Unified Parkinson's Disease Rating Scale) are excluded. Controls participants were healthy in the sense of behavioral and cognitive disturbances.

In the designed clinical protocol the participants have to undertake a set of physical activities and IADLs in a Hospital observation room furnished with home appliances. The clinical protocol activities are divided in three scenarios are as follows:

(1) Scenario 01 - Directed activities (10 minutes): it intends to assess kinematic parameters about the participant gait profile (*e.g.*, static and dynamic balance test, walking test);

(2) Scenario 02 - Semi-directed activities (15 minutes): it aims to evaluate the degree of independence of the participant by taking and organizing a list of daily living activities (IADLs) within 15 minutes. Participant is alone in the room with the list of activities to perform, and he/she is advised to leave the room only when he/she has felt that the required tasks are completed;

(3) Undirected ("free") activities (5 minutes): it aims to assess how the participant spontaneously initiates activities and organize his/her time.

The proposed monitoring system is tested with the video recordings of the Semi-directed scenario (Scenario 02). Table 1 shows the set of IADLs that the participant is instructed to perform. Results using a previous version of the clinical and a video-based approach for activity detection be seen in [19].

TABLE 1. CLINICAL PROTOCOL – SCENARIO 02

Watch TV,
Make tea/coffee,
Write the shopping list of the lunch ingredients,
Answer the Phone,
Read the newspaper/magazine,
Water the plant
Organize the prescribed drugs inside the drug box according to the daily/weekly intake schedule,
Write a check to pay the electricity bill,
Call a taxi,
Get out of the room.

B. Data recording

Experimental data is recorded using a 2D video camera (AXIS®, Model P1346, 8 frames per second), a 3D camera (Kinect® sensor), a motion sensor (MotionPod®), and ambient audio microphone (Tonsion, Model TM6, Software Audacity, WAV file format, 16bit PCM/16kHz). The proposed approach is tested with 9 participants (healthy: 4, MCI: 5).

MotionPod® is a proprietary device that provides estimation about a person posture based on the readings coming from accelerometers and gyroscopes sensors. MotionPod® is attached to Patient chest using a chest strap accessory. As Video and MotionPod® recordings are acquired using different computers, these computers had their internal clock reference automatically synchronized using a network service (Network Time Protocol) to avoid time issues.

C. Multi-sensor surveillance system

The proposed multi-sensor system is divided in two main components: the vision and the event detection components. The video record is processed by the Vision Component which is responsible to detect mobile objects and classify them according to a set of objects of interest (*e.g.*, person). Once a person is detected on the video frame under analysis, the event module component analyzes his/her activity in relation to the activity models previously defined by an expert using an ontology language. Posture events coming from MotionPod® data are taken in account only at the event component level. Fig. 1 illustrates a diagram of the system architecture and sensors contribution for each module.

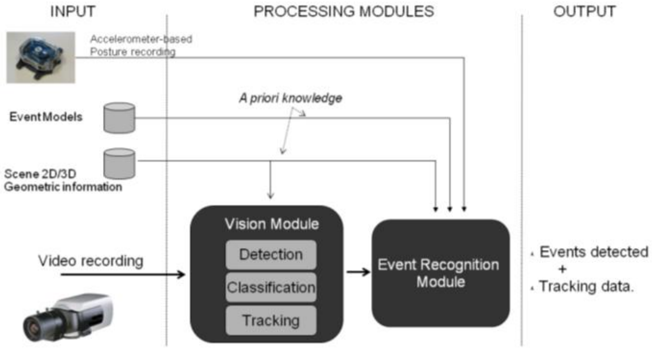

Figure 1. System architecture

1) Vision Component

The vision component has been developed using a modular vision platform locally developed that allows the test of different algorithms for each step of the computer vision chain (*e.g.*, video acquisition, image segmentation, physical objects detection, physical objects tracking, actor identification, and actor events detection). The vision component extracts the objects to track from the current frame using an extension of the Gaussian Mixture Model algorithm for background subtraction [26]. People tracking is performed by a multi-feature tracking algorithm presented in [20], using the following features: 2D size, 3D displacement, color histogram, and dominant color. Fig. 2 shows an example of the vision component output. Rectangle envelope highlights the detection of a person in the scene. Blue dots represent previous positions of the detected person in the scene.

Figure 2. Multi-sensor activity recognition system screen. Rectangle envelope highlights the detection of a person in the scene. Blue dots represent previous positions of the detected person in the scene.

2) Event Detection Component

Event detection component uses a generic constraint-based ontology language to model and recognize activity events. Event models are described using *a priori* knowledge about the experimental scene (scene model), the clinical protocol activities (event models), attributes of the physical object tracked by the vision component (*e.g.*, spatial, temporal, kinematic and appearance properties), and posture estimations coming from MotionPod® sensor.

The *a priori* knowledge about the experimental scene consists of the decomposition of a 3D projection of the scene floor plan in a set of spatial zones which represent contextual information about the clinical scenario (*e.g.*, zoneTV, zoneArmChair, zoneOfficeDesk). The constraint-based ontology is declarative and intuitive language as it is based in natural terminology, allowing domain experts to easily define and modify the event models.

Event models are hierarchically categorized according to their complexity (primitive or complex) and the information they model (the current state or time-based event). Primitive states refer to a specific value in the property(ies) of a tracked physical object (*e.g.*, the participant). Primitive events refer to a change(s) in the value(s) of an object property(ies) (*e.g.*, change of posture). Composite/Complex events are defined as a set of primitive events and/or states. More details about the generic ontology language used are seen in [25].

Table 2 shows an example of the complex event called "Person standing and using OfficeDesk". The ontology event description is divided among four components: the Physical objects involved in the event model (an object classified as a Person – p1, a contextual zone – z1, and a contextual object – eq. 1); the Components (or sub-events) that must be detected for the Event Model identification (*e.g.*, Person_using_OfficeDesk); the constraints which components and physical objects attributes must hold (e.g., minimal duration of the event "Person using OfficeDesk"); and an Alarm category used as reference to a specific treatment that could be performed in case of the event is detected.

TABLE 2. EVENT MODEL OF PERSON_STADING_AND_USING_OFFICEDESK

```
CompositeEvent(Person_standing_ and_using_OfficeDesk,
   PhysicalObjects(
            (p1 : Person), (z1 : Zone),  (eq1 : Equipment))
   Components(
            (c1 : CompositeEvent Person_using_OfficeDesk(p1, z1, eq1))
            (c2:  PrimitiveState     Person_standing_MP ( p1) )
    )
   Constraints((duration(c1) > 2)
   Alarm ((Level : NOTURGENT))
)
```

Table 3 describes the primitive state called "Person using OfficeDesk". "Person using Office Desk" event is modeled based on the participant presence inside the contextual zone "OfficeDesk", and in the distance between participant 3D bounding box projection on the scene floor and the parallelepiped modeling the real desk.

TABLE 3. EVENT MODEL OF PERSON_USING_OFFICEDESK

```
CompositeEvent(Person_using_OfficeDesk,
     PhysicalObjects( (p1 : Person), (z1 : Zone), (eq1 : Equipment))
     Components(
               (c1: PrimitiveState Person_Inside_Zone_OfficeDesk(p1, z1))
               (c2: PrimitiveState Person_closeTo_OfficeDesk(p1, eq1))
  )
  Alarm ((Level : URGENT))
)
```

3) Multi-sensor event fusion

Sensor fusion can be performed at different levels, *e.g.*, data level (raw data combination), feature level (fusion of observation data from different sensors), or at decision level (fusion of events detected by different sensors) [24]. The multi-sensor fusion herein presented is performed at decision level. One advantage of sensor fusion at this level is the possibility of changing the sensor type without the need of change of event models, *e.g.*, postures could be defined as an attribute or a sub-event, the source of which could be replaced as soon as it keeps its label. Herein the posture status coming from MotionPod® and the Visual component are defined as attributes of the ontology model called "Person", and the specific changes in these attribute values are modeled as primitive events.

Raw MotionPod® is post-processed using MotionPod® manufacturer software which provides the set of participant postures during the experiment (e.g., standing, sitting, lying down, changing from a posture to another). The vision component estimates standing and sitting postures based on a sitting threshold applied over the person 3D height. The sitting threshold is manually defined per video (and patient) based on the visualization of the participant average sitting height. A time synchronization step is performed based on sensors (video and accelerometer) readings timestamps.

The choice of which sensor posture estimation is used per activity model was based in the analysis of the system activity recognition performance in the defined contextual zones. For example, goal-oriented events that are performed farther from the camera viewpoint, where the Person remains immobile used accelerometer posture estimation, and Event models that requires quick response in posture estimation (Sitting to Standing transfer tests) were modeled in respect to the vision module posture estimation, as the accelerometer standard data acquisition rate is around 1 data acquisition/sec.

4) *Events Models and IADLs*

Event models are described taking in account a person presence in a contextual zone, his/her proximity to a contextual objects, and his/her current body posture (*e.g.*, standing, bending). These constraints pose a limitation to some IADLs models as their target actions that cannot be directly detected (*e.g.*, writing a check to pay electricity bill, reading a magazine, organizing a set of cards) and they have the same contextual information.

In these cases, a few IADLs of the Clinical protocol are merged in a single activity. For example, answering and calling someone is a voice-based behavior in which the person interacts with an object (the phone), and, as there is none pressure sensor in the phone nor audio recognition in this approach, these two models are simplified to "using phone" activity. Table 4 lists the activity models of the clinical protocol (Scenario 02) and their simplified version.

TABLE 4. COMPARISON BETWEEN EVENT MODELS AND PROTOCOL IADLS

EVENT MODEL	MODELED EVENT
Person using OfficeDesk	▪ Make a shopping list of the ingredients for lunch ▪ Write a check to pay the electricity bill.
Person watching TV	▪ Watch TV
Person preparing Coffee	▪ Make Tea/Coffee.
Person using Pharmacy	▪ Organize the prescribed drugs inside the drug box according weekly to the hour/day schedule
Person using Phone;	▪ Call a taxi, ▪ Answer the Phone
Person watering Plant;	Watering the plant
Person using Reading Zone	Person reading the newspaper/magazine

D. *Evaluation*

Evaluation results are presented for event models based only on visual constraints and the Multi-sensor approach to evaluate the improvements in event detection performance. Vision-based models consist of the same activity models but only taking in account posture estimation obtained from visual information.

Activity recognition performance is assessed using the performance indices precision and sensitivity (Equations 1 and 2, respectively), where TP refers to True Positive events; FP to False Positive events, TN to True Negative events, and FN to False Negative events. The evaluation is performed for the 15 min. of each video sequence, and not in the form of previously extracted video chunks containing only IADL events.

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

III. RESULTS AND DISCUSSION

Table 5 shows the events detection performance rate for the vision system approach about 9 participants (15 min. each). GT states for ground-truth, and it specifies the total number of events inside the video sequences of all participants. The term "Person" was omitted from the event model name to improve the table readability. Table 6 shows the event detection rate for the multi-sensor approach.

TABLE 5. ACTIVITY DETECTION RATE OF THE VISION SYSTEM

Activity	GT	Precision (%)	Sensitivity (%)
Standing and preparing Coffee	13	37.5	37.50
Sitting and using OfficeDesk	8	5.80	100.00
Standing and using OfficeDesk	12	43.37	100.00
Standing and using Pharmacy	8	75.92	100.00
Standing and using Phone	19	83.33	25.92
Standing and watering Plant	10	100.00	100.00
Average performance	70	57.65	77.23

TABLE 6. ACTIVITY DETECTION RATE OF THE FUSION SYSTEM

Activity	GT	Precision (%)	Sensitivity (%)
Standing and preparing Coffee	13	51.85	100
Sitting and using OfficeDesk	8	27.22	100
Standing and using OfficeDesk	12	43.37	100
Standing and using Pharmacy	8	75.92	100
Standing and using Phone	19	83.33	100
Standing and watering Plant	10	100.00	61.11
Average performance	70	63.61	93.51

The vision system has an average precision of 57.65% and a sensitivity of 77.23%. The multi-sensor system performance is higher at the two indices, 63.61% at precision and 93.51% at sensitivity, highlighting that the use of accelerometer data in posture estimation has increased the overall system performance by improving the precision of the first three events of Table 6.

Factors like occlusion, illumination changes, and color clothing similar to background have reduced person body detection at visual component, increasing the difficult at determining posture. Accelerometer data acquisition resolution is sometimes not sufficient to cope with person speed, e.g., in changing postures activities. But, the use of both sensors, each one applied in the situation (event model) where it provides better estimation, have improved the overall system performance without incorporating noisy in the event estimation framework.

Part of the FP events that caused lower values of precision could be explained by unexpected behaviors of the participants that are not predicted in the event models. For example, events based on the spatial zone “OfficeDesk” are affected by this zone proximity to the “Watching TV” zone. FP events of “Using pharmacy” events are explained by a few patients placing a chair into this zone to watch the TV (located in the opposite side of the room). These inconsistences will be future addressed by refining the event and scene models and by the adoption of new features (e.g., adding an orientation attribute to the “Person” model and place constraints avoiding the cited FP event).

IV. Conclusion and Future Work

The preliminary results of the proposed system shows that the adoption of a multi-sensor approach (a video data complemented by a wearable accelerometer) has improved the event detection performance of the activity recognition system in comparison to the same system based only on video data.

Future work will focus at analyzing an unsupervised way of choosing among the posture attributes based on reliability measurement. A reliability measurement could support the automatic choice of one sensor over the others or the calculation of the likelihood of events based on multiple sensors reading. A broader validation is also planned to evaluate the reproducibility of results shown in a larger quantity of patients. The proposed multi-sensor approach also added new posture types (e.g., bending, lying down) that will be considered in the next evaluation. The long-term goal of the proposed approach is to support clinicians in the identification of emerging symptoms that could early diagnose Alzheimer patients at mild to moderate stages in a quantitative and objective way.

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