Different sADL Day Patterns Recorded by an Interaction-System Based on Radio Modules

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Abstract. In this contribution different behavior patterns of different people are being analyzed. They are recorded by a system with small units based on a microcontroller and radio modules. Due to the demographic change, there is a need in Germany for systems that give elderly people the opportunity to live an autonomous life for as long as possible. There is a great demand of supporting systems that are able to ensure medical safety for these people. In order to determine the health state of a person an obvious choice would be to draw conclusions from the behavior patterns which can be deduced from the ADL (Activities of Daily Living). Different technologies are available for recording ADL. Some of them are presented in this paper. Following that, the system “eventlogger” will be introduced and the interaction of patients, mapped in a geriatric day hospital, and the resulting behavioral patterns, will be analyzed.

1 Introduction

In Germany, as well as in all other industrial nations, new challenges in the care and health systems will have to be met, due to the change of age distribution. In an ageing society there are more and more elderly people in need of care on the one hand and less young people who work on the other. This results in higher financial burdens for the social systems as well as the need for more personnel. For these reasons, along with the desire for autonomy, there is the wish to enable elderly people to live in charge of themselves and autonomously in their own home. In order to give these people security as far as their medical treatment is concerned an early diagnosis of old-age illnesses is essential.

5% of the people over 65 and 40% of those over 90 suffer from dementia for example [1]. Alzheimer dementia is usually a chronic illness characterized by a reduction in mental performance and memory recall and the implications this has for everyday activities (ADL) [2].

In order to test ADL there is a choice of standardized questionnaires like the Barthel Index for example [3]. This index describes an activity such as going to the toilet as follows: *“Patient is able to get on and off the toilet, fasten and unfasten clothes, prevent soiling of clothes, and use toilet paper without help. He may use a wall bar or other stable object for support if needed. If it is necessary to use a bed pan instead of* *a toilet, he must be able to place it on a chair, empty it, and clean it. Patient needs help because of imbalance or in handling clothes or in using toilet paper"* [4]. Besides defining the ADL for the diagnosis of dementia, watching the ADL can also illustrate the course of an illness and successful therapy. Thus ADL scales are being increasingly used as a criteria for the choice of therapy. Hence comes the wish to have an objective and automated method of defining the ADL at hand.

For initial tests it would be far too time consuming to map all the activities described in the Barthel index with the aid of a technical system, and thus the "simple ADL" (sADL) was introduced [5]. Here, from the interaction with an object (e.g. a toilet) the resulting sADL can be deduced.

In this article the first results from implementing the system referring to [6] shall be introduced. For this the day time profiles of different persons were observed and evaluated. Fortunately nearly every profile correlated to a specific person.

2 State of the Art

As already mentioned, the ADL are nowadays found using ADL scales according to the Barthel Index, in order to determine the autonomy of a person. Here data is collected by asking questions about the ability to carry out daily routines. The questionnaire is filled out by the patient if possible, or by a relative or nurse.

The subjectivity is one of the greatest disadvantages. [7] verified that a pure patient survey by the doctor is not significant. The Barthel Index scores surveyed by the patients` nursing staff were therefore compared to the direct interviews of the doctors. There were significant differences, probably due to the embarrassment of the patient on the one side and to the subjectivity on the other. [8] also published a study in which they used different kinds of data (patient, nursing staff, relatives, doctor) to determine the ADL scales. As a result, it is determined that the source of information for determining people's extent of activity is not interchangeable and that patients often overestimate their functional performance, whereas external observers often underestimate the activities. Another disadvantage of these ADL scales is, that they are usually applied only when a person is already in treatment. Thus at the onset of the disease the gradually deterioration cannot be recognized. However, it is generally known that the therapeutic results are better the sooner a disease is detected.

In research there are various projects with the aim of developing a system which is able to detect different ADLs automatically. Here, one method is to define areas of frequent use with the aid of infrared motion detectors [9-13]. These motion detectors are either installed in the living area or connected via radio transmission and batteries without using cables. As the areas under surveillance can only be roughly defined, additional sensors, such as door contacts are used to attain more exact information. Another approach is based on video systems. Certain areas of the living environment were recorded like in [14] and then evaluated using algorithms. In order to attain better results the video systems are also combined with switches [15] [16] as well as with RFID-Systems [17] [18]. A lot of research work is done using RFID-technology. [19] for example, developed a glove and, later on, a wristband equipped with RFID-readers [20]. The readers have a range of about 10 cm. [21] also developed a mobile RFID-system that was worn around the wrist and had a similar range. [22] [23] were able to significantly increase the recognition of ADL through combination with an acceleration sensor. A gap in the recognition of the RFID-system can be filled by using the acceleration.

A disadvantage of the infrared motion detectors is that they cannot differentiate between two different human beings. Sometimes there are even problems in differentiating humans and pets. Video systems have problems when covered and with different kinds of lighting. What is more, the acceptance of these systems is doubtful. By adding further technologies the disadvantages of video systems can be reduced, the installation work and the complexity of the data involved however will increase significantly. RFID-systems prove not to be useful in everyday life, due to their short range.

3 Materials and Methods

The system "eventlogger" which is used here, is based on adjustable and local communication between radio modules and was already presented already in [6]. The basic approach is a blueprint of human communication. The volume of the voice is always chosen in such a way that the persons you are talking to are being reached and not the complete room. This approach was already implemented in robotics via infrared [24]. The transmit power of the used radio modules with 2.4Ghz can be adjusted to different ranges. The modules are transmitting their own ID with the adjusted power. The transmit power can be adjusted in 64 steps with the following values:

$$-33\text{dBm} < TP < 0\text{dBm} \tag{1}$$

With the hardware used in this setup we get ranges r_{sADL} from about 0.3 to 40 meter. Hence the usual measuring of the RSSI (Received Signal Strength Indication) is not used.

The transmitting of the own ID is done with a frequency of f_t=2 Hz. At the same time the radio modules are able to receive the ID of other eventloggers with a frequency of 0.5 Hz and a duration of 501ms. Hence, two Eventlogger (m,n) with different positions P in a room, have three different states:

$$P_m \begin{pmatrix} x_m \\ y_m \\ z_m \end{pmatrix} ; P_n \begin{pmatrix} x_n \\ y_n \\ z_n \end{pmatrix} ; \; r_{sADL_m} > r_{sADL_n} \tag{2}$$

State 1: Both Eventlogger are outside of the transmit range of the other:

$$|P_m| - |P_n| > r_{sADL_m} > r_{sADL_n} \tag{3}$$

State 2: Only one Eventlogger can receive the other:

$$r_{sADL_m} > |P_m| - |P_n| > r_{sADL_n} \tag{4}$$

State 3 Both Eventlogger can receive the other:

$$r_{sADL_m} > r_\mathrm{n} > |P_m| - |P_n| \tag{5}$$

The event E_m is generated when the distance of both Eventlogger is smaller than the transmit range r_{sADLm}:

$$|P_m| - |P_n| < r_{sADL_m} \Rightarrow E_m \tag{6}$$

If the Event E_m not detected anymore, a $sADL_m$ is saved. The advantage of saving the event at the end is having an efficient usage of the memory and an easier understanding of the raw data. That is why the ID, the starting time and the duration is saved.

$$sADL_m := [ID_m, k_{on}, k_{off} - k_{on}] \tag{7}$$

K_{on}: starting time; k_{off}-k_{on}: duration

The sADL are saved on the flash memory of the Eventlogger or on a separate Micro-SD-card. In addition every name of each ID is saved for a better allocation of the data.

As already mentioned, the data can be read out as a text file directly from the SD-card. Furthermore the data can be sent to a base station connected to a PC or the HomeCareUnit (HCU) [25]. There they are saved in a sql-database and visualized via different illustrations [26]. There is a day view and a detail view of the sADL. The day view shows the total duration of the interactions to other Eventlogger (Fig.2). The detail view shows the duration of each interaction in a time diagram (Fig. 3).

The hardware setup of the eventlogger is designed as followed: The central unit is a nanoLOC AVR module which consists of an atmel microcontroller (2) and a radio chip (1) as well as a chip antenna. To determine the proper time a Real-Time-Clock (5) is connected via I2C. The data can optionally be stored on an external flash memory or on a mini SD card (4), which are connected to the microcontroller via SPI. Additionally a motion sensor (3) is integrated to be able to determine states of motion [27] in the future. Movements of objects such as the cup could also be observed. The power supply (6) is assured by a lithium-ion battery with 250mAh, a charge controller and a voltage converter (Fig. 1).

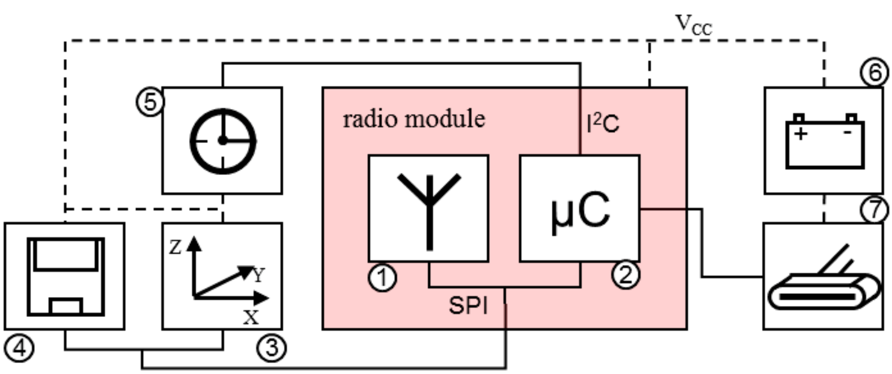

Fig. 1. Hardware setup eventlogger 1)Radio chip, 2)Microcontroller, 3)Accelerometer, 4) Flash-memory/SD-card, 5) Real-Time-Clock, 6)Battery, 7)Connector

4 Experiment

The system that is introduced here was installed for evaluation at the Gerontopsychiatric Day Clinic of the TU-Munich (Clinic for Psychiatry and Psychotherapy) for a period of two month. At the Gerontopsychiatric Day Clinic people with affective and dementia illnesses are treated over a period of four to eight month, applying a multimodal therapy program.

The following objects or rooms were equipped with an eventlogger:

- kitchen
- conference room
- nurse's room
- men's toilet and wash basin
- ladies' toilet and wash basin
- entrance (one inside one outside)
- occupational therapy room
- PC
- physiotherapy room
- 5 mobile eventlogger for distribution to patients

For the evaluation 5 volunteers (four students and a 60 year old person) each wore an eventlogger in the rooms of the day clinic and they were each accompanied by a person keeping minutes. They had the task of noting the time that the actions took place. In the end the data noted by the eventlogger and the minutes were compared. It was shown that a sensitivity of 80% with a weighting of short events detection can be reached within this experimental setting. Also a sensitivity of 79.9% and a specificity of 99.2% with a weighting of long events detection could be reached [5].

In addition different patients in the day clinic wore an eventlogger for a couple of days each. From 28 persons 82 day profiles were produced. At first we will only look at the first two weeks during which 12 people produced 41 day profiles. Fig.2 shows a day summary, Fig. 3 a day profile.

Using the profiles attained in this way, it was first determined whether they were specific to an individual person. 41 day profiles were shown to a Doctor over a period of two weeks and he arranged them without any further information. The Doctor assigned the profiles to 12 people, which was the exact number. Important criteria for the distribution were: Frequency and time of going to toilet, interaction with others, general conduct.

In a further step the persons were characterized according to their day profiles and this was compared to the notes of a medically trained observer.

As expected, the basic behavior of an individual can easily be ascertained. Partly, it can be deduced from the whereabouts of a person. Thus it is implied that when a person is in the kitchen or conference room, he or she is sitting down. If the entrance is logged and then there are no new events for some time, it is implied that the person was outside and has most likely taken a walk. Furthermore the number of interactions with other people is also an indicator for the basic behavior. Staff, like for instance the nurse or the occupational therapist, could be recognized due to their individual daily

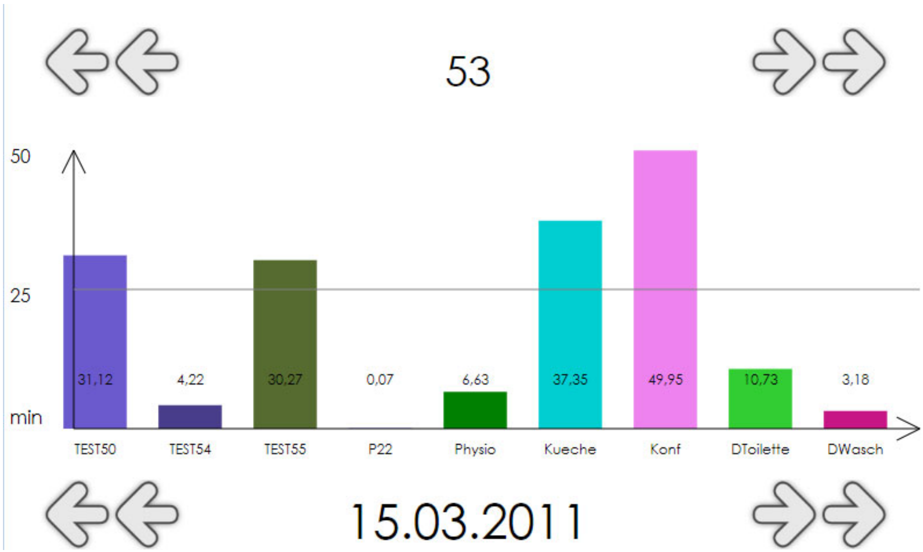

Fig. 2. Summary of the day view of proband 5

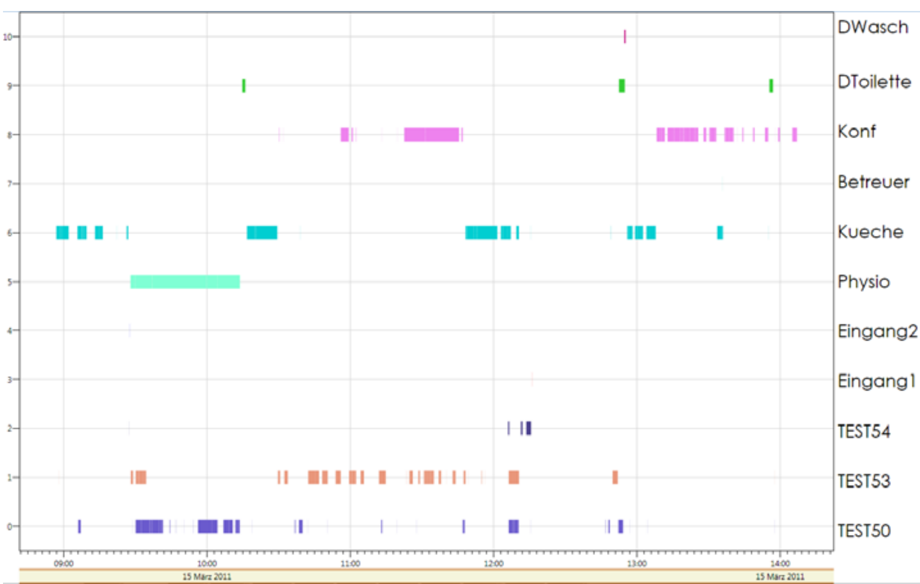

Fig. 3. Day profile of proband 5 in detail view

Table 1. Interpreted information by a doctor from the day profile taken from the eventlogger versus the notes form the clinical practice

Pers.	day profile taken from the eventlogger	notes form the clinical practice
1	basic passive behavior	sits much at the same place
	elderly female proband	middle aged woman
	about 1x per day on toilet	
	4th day 1 hour on the PC	proband has been told to work on the PC for 15min
2	more active basic behavior	old but very agile
	2x walk outside alone	
	Walk outside with others	social excursion
	at least 3 times per day on toilet	has been told to go to toilet 4x
3	active basic behavior	young, mobile, moving rapidly
	maybe a smoker	smoker
	walks with proband 11	
	goes to the toilet at different times	The information about going to toilet given by the proband and recorded by the eventlogger differ
4	basic passive behavior	inactive
		no (no suggestions)
	approx. 3x toilet per day, extended periods	
	little contact with other	mentally severely impaired
	often goes home early	proband gets nervous after lunch, is taken home earlier
5	1 day 7x toilet	aconuresis
	2 day 4x toilet	order only 4x toilet
	in the kitchen and conference room a lot	severely impaired
	together with person 10 a lot	
6	2x a day longer time on the toilet	
	longer talk with the carer	sociable
	much contact with other persons	sociable, helpful
	walks outside	mobile, fit
7	carer (between supervisors room, kitchen, conference room)	nurse
	accompanies patient in the cellar for physio-therapy	

Table 1. *(continued)*

8	short recording lot occupational therapy -> occupational therapist	occupational therapist
9	often at the entrance -> smoker spends a lot of time in the conference room longer walks alone rarely goes to toilet ->drink more?	smoker insecure in the group young, likes to be alone onset of Alzheimer
10	approx. 3 times per day toilet often takes a walk outside	likes go for a walk dementia
11	Rarely goes to toilet	little intellectual restriction mainly depressive young, healthy
12	many contacts with other people	sociable, friendly onset of dementia

routine. Nothing, however, could be said about the current course an illness was taking, due to the short periods of mapping over only a few days. This however is the aim, with the aid of the system that is being introduced here, the daily routine of a person and possible changes over a longer period of time should be detected. Aconuresis (incontinence of the bladder), as in person 5 could easily be noticed. In addition individual persons were given certain tasks that could be verified with the help of the eventlogger. Person 5 for example was asked to go to toilet exactly 4 times, and this was done correctly. Person 1 was asked to work at the computer for 15 minutes. This was done more than to standard, by working there for an hour.

5 Discussion

The day profiles of individuals have been shown to differ to such an extent, that a Doctor can differentiate them, at least if there is a limited number. As this analysis is very time consuming however, it will be necessary to develop an algorithm that enables changes in a person to be detected automatically. Here it will be important to allow a learning phase in which the "normal" behavior can be determined. It only takes a few days to discover basic kinds of behavior and conditions such as aconuresis by looking at the rate at which the toilet being used. Due to the limited number of day profiles however it is not possible to draw conclusions, as to whether slow changes within the system would be recognized by a Doctor or whether an algorithm would detect them. For this more experiments will be necessary. The results so far, however, seem to be very promising. What is more, the system can, contrary to other state of the art devices, be easily integrated into living areas and comes at a realistic price.

6 Conclusion

The newly developed system eventlogger uses radio modules with an adjustable range and serves as a recorder for sADL. The first trial runs at the Gerontopsychiatric Day Clinic of the TU Munich have shown that the recorded sADL and the then resulting day profiles can be differentiated due to their individuality. What is more, personal basic habits and abnormalities (in using the toilet) can be detected. The trial run that was made here shows that the behavioral patterns of the patients are individual to such an extent that a differentiation is possible. The next step will be to develop an algorithm which will do this automatically and is able to detect changes. Furthermore it shall be tested whether the system can be used as an aid to train people with aconuresis. Such a training program aims at prolonging the time intervals between each visit to the toilet (e.g. to two hours). To do that, the eventlogger will indicate the end of a time interval via an LED lighting up (if in the meantime going to toilet has not been registered) and thus “allows” a visit to the toilet. By this setting a training effect can be reached that gradually prolongs the intervals between going to toilet and will thus support a behavioral therapy treatment of aconuresis.

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