**Intelligent elderly-care prototype for fall and disease detection**

**Abstract**

**Background:** The number of elderly people in need of help with the activities of daily living in the EU is rapidly increasing, while the number of young workers is decreasing. Elderly care will, therefore, also have to be provided by intelligent computer systems.

**Methods:** A prototype elderly-care system, developed at the Jožef Stefan Institute, mostly as part of the Confidence project, is presented. The prototype detects falls and behavior changes in the elderly. It learns from experience and is based on intelligent interpretation of movement patterns. Three sets of tests were performed to evaluate its properties on various subjects when engaged in normal activities, falling and imitations of several health problems under medical supervision. The key novelty was in location based sensors and advanced intelligent methods.

**Results:** The prototype using the Ubisense sensor system, which detects the locations of tags worn on the body, correctly recognized 96 % of falls, significantly outperforming simple accelerometer-based systems. In addition, it recognized up to 99 % of abnormal behavior.

**Conclusions:** Experimental results showed that an intelligent system coupled with advanced location sensors can achieve the level of performance needed in real life. The system offers significantly better performance than commercially available solutions, and once the price of sensors decreases, its widespread application seems likely.

**Introduction**

Slovenia will have more than 511,000

people aged over 65 years by 2030 and

135,000 of them will be over 80.1,2 Accord

ing to the Administration on Aging, 19 % of

people over 65 face limitations when per

forming the activities of daily living, and 4 %

of them have severe disabilities.3 The num

ber of people that can receive institutional

healthcare, however, is only 18,000, and the

number of people that can receive help at

home is only 7,000.4 A strategy for advanced

health care is being prepared in Slovenia as

the second Bill on the Permanent Care and

Insurance for Sustainable Supply.4 Intelli

gent systems in the field of ambient assisted

living (AAL) can play an important role in

sustainable elderly care. Some are already

commercialized, such as Dom IRIS at the

Institute for Rehabilitation in Slovenia.5 The

elderly, however, may require 24-hour mon

itoring in order to be able to detect falls, diz

ziness, illness, unusual behavior due to de

mentia, etc. These issues are not addressed

adequately by the current AAL systems,

so more advanced solutions are needed.

Mostly as part of the Confidence project,

we developed a computer-aided prototype

for 24-hour monitoring of falls and unusual

behavior in the elderly, which was shown

to automatically detect many of the health

problems they commonly suffer from.

**Background**

Computer-aided approaches for elderly

care are typically structured in three lay

ers: sensors to capture the data on the user’s

situation, interpretation methods (software)

to “understand” the situation, and services,

which provide help or intervention based on

the system’s understanding of the situation.

Sensors set the upper limit on the perfor

mance of the system because they determine

what can be learned about the user’s situa

tion. Sensors differ in their accuracy, obtru

siveness and cost. An important group of

sensors monitors the user’s movement. Ac

celerometers measure accelerations, which

can be used to detect the impact due to a fall,

or the orientation of the body by measuring 826 Zdrav Vestn | november 2011 | Letnik 80

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Two important issues in the design of

elderly-care systems are their accessibility

and portability. The first issue is tackled by

user interfaces and assistive technologies

that give elderly and disabled users access to

electronic devices.13 Regarding the second

issue, the portable systems tend to rely on

smart mobile phones.14

The existing systems and methods typi

cally implement simple functions such as

opening doors on request or when a sensor

detects proximity. In addition, they imple

ment simple fall detection based on acceler

ometers. When tested in laboratory condi

tions and on straightforward cases of falls,

the systems achieve a very high accuracy.

However, they are usually not tested in com

plex real-life situations. As a consequence,

in real use, accelerometer-based methods

tend to raise false alarms in cases such as

sitting quickly on a chair. Furthermore, the

presented systems do not collect mid- and

long-term data and therefore fail to recog

nize that, for example, the user is limping.

To improve upon the research described

in this section, the system presented in this

paper was developed using intelligent meth

ods to observe short-, mid-, and long-term

behavior. It is able to recognize falls and

behavior changes and automatically raise

alarms and warnings.

**Methods**

The presented approach was tested with

the permission of the National Medical Eth

ics Committee, approval 45–46/12/08. The

three sets of tests reported here were con

ducted in experimental conditions at the

Jožef Stefan Institute in a laboratory measur

ing 5 × 3 meters by healthy, young volunteers

able to simulate falls and health problems as

instructed by a physician. These tests in

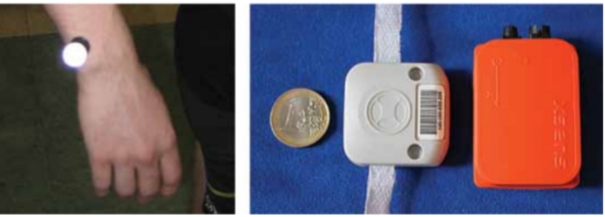
cluded hundreds of hours of recordings over

a period of two years. The system has been

implemented and tested in several European

countries, and is currently being intensively

tested on the elderly at their homes in Italy.



The first set of tests included five per

sons—four male (24y, 24y, 31y, 26y) and

one female (27y)—who imitated falls and

four health problems: hemiplegia (hemipa

and user-friendly interfaces, but are only ca

pable of limited autonomous action. Others

are capable of reasoning about the user and

the environment, and acting autonomously.

They may also learn and improve their per

formance on their own.

Soprano was a European 6th Frame

work Programme project that aimed to

design and develop a set of smart services

with natural and comfortable interfaces for

the elderly.9 The developed prototype shows

the visitors at the door on the television, re

minds the user about important tasks to be

carried out, e.g., taking pills, etc. The MKS

Electronic Systems collaborates in the proj

ect “Independent Residing enabled by Intel

ligent Solutions” (IRIS), which aims to en

able the elderly and people with disabilities

to achieve functional independence and live

independently.5,10 The developed electronic

devices enable the control of the living space,

i.e., opening doors and windows, control

ling television and radio, turning heating on

and off, etc. The University of Florida has a

Smart Home that demonstrates the concept

of automated help and care for the elderly.11

The Smart Home includes devices perform

ing tasks such as water-leaks detection, vid

eo tracking of visitors, checking if the house

is secured, and voice-controlled door lock

ing and unlocking.

Intelligent systems typically observe only

short-term events such as falls. Bourke et al.

investigated the acceleration data produced

during the activities of daily living and dur

ing falls.8 The data were recorded by young

subjects performing simulated falls. The

data analysis showed that by defining an ap

propriate threshold, the accelerations during

the falls and the accelerations produced dur

ing the normal activities of daily living can

be distinguished. In similar publications, ac

celerometers with a simple threshold are of

ten reported to achieve close to 100 % accu

racy for typical falls. Perolle et al. described

an elderly-care system that consists of a mo

bile module worn by the user, which is able

to locate the user and detect falls.12 The de

vice is connected to a call centre, where the

data are analyzed, and emergency situations

are managed. The initial tests showed that

over 90 % of falls were recognized correctly

with straps. In addition, the acceleration of

the accelerometer worn on the chest was

tracked. The Xsens accelerometer is a high

end device costing about €2,000, but in our

experience devices costing €200 perform no

worse at fall detection. In total, 200 events of

falling (tripping, falling slowly, falling from

the chair) and 300 events of normal behav

ior (sitting down normally and quickly, ly

ing down normally and quickly, searching

for something on the floor on all fours) were

recorded. We aimed to select a mixture of

easy- and difficult-to-recognize falls, and a

few normal events that resemble falling or

lying after a fall.

The third set of tests included four per

sons — three male (31y, 27y and 25y) and one

female (28y) — who imitated falls and the

previously mentioned four health problems:

hemiplegia, pain in the leg, pain in the back

and Parkinson’s disease. These recordings

were captured with the Ubisense system at

10 Hz tracking four tags: waist, chest and

both ankles. In total, 80 sequences of nor

mal behavior (20 of walking normally, 20 of

sitting down and standing up normally, 20

of lying normally, 20 of rearranging objects

on a table) and 80 recordings of abnormal

behavior (20 of walking with each of the

four health problems) were recorded.

Tags belonging to the Smart and Ubisense

systems and an accelerometer are shown in

Figure 1. The Smart and Ubisense tags are

tracked by sensors mounted on walls, which

were connected to a personal computer. The

accelerometer transmitted the data to the

computer over a short-range wireless con

nection. The Ubisense system can track tags

within one apartment if the interior walls

are not too thick or contain a lot of metal;

resis), pain in the leg, pain in the back and

Parkinson’s disease. These imitations were

performed explicitly following typical clini

cal pictures as described in textbooks. Real

patients may show less typical movement

patterns, but in the initial experiments base

line performance had to be established. The

recordings were captured with the Smart

sensor system at 10 Hz with 12 tags attached

to the wrists, elbows, shoulders, hips, knees

and ankles (on the skin or on tight-fitting

clothing). Since the elderly prefer as few tags

as possible, we examined the performance

of the prototype with a reduced number

of tags.15 Furthermore, the Smart system

is very accurate, but it is impractical be

cause of the high price and because it needs

a direct line of sight between the tags and

wall-mounted sensors. Therefore, we added

normally distributed noise to the recorded

data to simulate less accurate and cheaper

equipment. We were particularly interested

in a comparison with the Ubisense sensor

system, which is why we measured the noise

in multiples of Ubisense noise. In total, 165

sequences of falling (tripping, falling slowly,

falling from the chair, etc.), 70 recordings

of lying down, 25 sequences of sitting down

and standing up, 25 sequences of walking

normally and 100 sequences of walking ab

normally (25 with each of the four health

problems) were recorded.

The second set of tests included 10 per

sons — six male (26y, 32y, 26y, 26y, 23y and

24y) and four female (27y, 26y, 33y and

28y)—who imitated falls. These record

ings were captured with the Ubisense sys

tem and with an Xsens accelerometer, both

at 10 Hz.16 The locations of four Ubisense

tags attached to the waist, chest and both

ankles were tracked. The tags were attached 828 Zdrav Vestn | november 2011 | Letnik 80

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**Figure 2:** Accuracy of the

short-term data analysis

detecting falls.

**Figure 3:** Accuracy of the

mid-term data analysis

recognizing unusual

behavior in general.

an alarm should be triggered if the user is

lying immobile for a prolonged time in an

unusual place) and two machine-learning

classifiers, namely C4.5 and Support Vector

Machine (SVM).22

The mid-term data of a few minutes are

used for the analysis of the user’s posture and

movement in order to recognize hemiplegia,

pain in the leg, pain in the back, Parkinson’s

disease and generally unusual behavior. To

recognize the four specific health problems,

the prototype computes various distances

and angles between the parts of the user’s

body.16,23 Based on these, an SVM machine

learning classifier decides which — if any —

of the four health problems the user has.

To recognize unusual behavior in gener

al, the prototype collects statistics about the

user’s movement and builds a personalized

model of usual behavior. If the user’s behav

ior significantly deviates from the usual be

havior, this may indicate a health problem,

e.g., if the user begins to limp, he/she might

have had a stroke. The degree of deviation

is computed with the Local Outlier Fac

tor (LOF) algorithm.24 The collected statis

tics characterize the user’s gait (speed and

length of a step etc.), turning (speed, angle

etc.), walking speed, general speed of move

ment, and the speed of transitions between

postures.

The long-term data are used to analyze

deviations in the pattern of the activities of

daily living, which can indicate deteriora

tion in health. It is implemented similarly to

the mid-term data analysis, except that the

observed statistics characterize the activities

the user is performing in the various rooms

in the apartment.

When a fall is detected, the intervention

service sends an alarm to caregivers. The

user can cancel the alarm, if the prototype

was mistaken and there is no hazardous

situation, by pressing a button on a porta

ble device similar to a cell phone, which is

a part of the prototype. If the alarm is not

cancelled, the caregivers are informed of the

circumstances in which the alarm was sent.

In addition, if a deviation in behavior is rec

ognized, the prevention service informs the

caregivers by sending the information on

the usual and unusual behavior.

however, the accuracy decreases in propor

tion to the number of obstacles.17

The data was processed by a novel intelli

gent real-time elderly-care prototype called

Confidence, which was implemented at the

Jožef Stefan Institute. This prototype repre

sents the main achievement of the European

7th Framework Programme project Con

fidence.18,19 It detects falls, recognizes un

usual behavior and a set of health problems.

The core contribution of this prototype is

the interpretation layer. It receives data from

different sensors, typically at 10 Hz. The data

are the positions and/or accelerations of tags

attached to the user’s body. Firstly, the data

are preprocessed to synchronize multiple

sensors, reduce sensor noise and extrapolate

the locations of missing tags. Secondly, the

posture of the user, e.g., sitting, standing and

walking, is predicted with the Random For

est machine-learning classifier and expert

knowledge in the form of rules.20,21 Finally,

the data are analyzed for all three observa

tion periods.

The short-term data of a few seconds are

used to recognize falls of several types: trip

ping, fainting, falling from the chair etc. The

falls are recognized using expert rules (e.g.,

havior, in general. This means that all the

recordings of behavior with health prob

lems are grouped together and the goal was

to distinguish them from the recordings of

normal behavior. Since the gait analysis did

not use the tags on the arms and we only

considered bilaterally symmetric tag place

ments, the number of tags varied from 8 to

2. One can see that the accuracy with eight

tags and little noise is above 99 %, but it de

creases quickly with fewer tags and higher

noise. This means that gait analysis requires

high-quality sensors.

Figure 4 shows the accuracy of the mid

term data analysis recognizing specific

health problems. The number of tags again

varies from all 12 to 1. One can see that the

accuracy is slightly lower than in Figure 3,

especially with fewer tags. This is to be ex

pected, since recognizing which specific

health problem a person has is more difficult

than recognizing that the person has some

health problem.

The second set of tests used the Ubisense

sensor system and an accelerometer to rec

ognize falls. The results are presented in

Table 1. They show that the prototype cor

rectly distinguishes between falls and nor

mal behavior with a 95.7 % accuracy when

using the Ubisense system and with a 57.2 %

accuracy when using an accelerometer. For

comparison, the Smart system using the

same four tags as Ubisense achieved a 93.5 %

accuracy.

The third set of tests again used the Ubi

sense sensor system to recognize unusual

**Results**

The first set of tests of the Confidence

prototype used the Smart sensor system

with up to 12 body tags and varying de

grees of noise added to the sensor data. The

results are presented in Figures 2, 3 and 4.

They show the accuracy with respect to the

number of tags (vertical axis) and the de

gree of noise (horizontal axis). The curves

in the figures represent the borders between

the areas with different accuracies. The ac

curacies were measured with 10-fold cross

validation.

Figure 2 shows the accuracy of the short

term data analysis detecting falls. The num

ber of tags varies from all 12 to 1. One can

see that in this test the number of tags does

not have a large impact on the accuracy of

the fall detection: it is around 95 % with all 12

tags and around 92 % with a single tag. Inter

estingly, the noise that was added to the data has an even smaller impact on the accuracy.

the accuracy of the mid

term data analysis recognizing unusual be

tects lying outside the bed, which this event

resembled.

Regarding the detection of unusual be

havior, the results show that with the Smart

system using the same four tags as the Ubi

sense system, normal and unusual behavior

can be distinguished with a 75 % to 90 % ac

curacy, depending on the degree of noise.

This was accomplished by analyzing the gait

characteristics only. With the Ubisense sys

tem, only a 64.6 % accuracy was achieved by analyzing the gait characteristics. However, when other statistics were added, an accuracy of up to 99.1 % was obtained.

The Ubisense system and accelerometers

are practical enough to be used by the elderly without assistance. Attaching and removing the devices is easy, and the only other task required of the user is changing the batteries. The tags belonging to the Smart system are more difficult to attach and should be attached within a few centimeters of the ideal location, so the elderly would likely need assistance. The recordings made with the Smart system require some manual postprocessing, although similar sensor systems exist that do not have this requirement. None of the devices can currently be worn in the shower or bath, but a water-proof design for elderly-care is technically not difficult, at least for the Ubisense system and accelerometers. In summary, the Ubisense

system and accelerometers are suitable for a home setting, whereas the Smart system – in its current form – is suitable for a laboratory setting.

The prototype can be easily integrated

into existing smart-home solutions such as

IRIS and the Smart home in Florida.5,11 This prototype—if deployed in a smart home— would represent a significant added value by improving the user’s confidence and independence since it acts as a 24-hour virtual caregiver, reassuring the user that he/she will get help when needed. However, in order for it to be deployed, it requires a computer and the installation of a sensor system.

**Conclusion**

This paper presents an intelligent, real

time, elderly-care prototype, which recog

behavior, like in the first test set. Table 2

shows the accuracy of several movement

characteristics, not only gait, as in the first

test set using the Smart system. One can see

that the gait characteristics result in a lower

accuracy compared to the Smart results,

which is probably due to using only four

tags and the lower accuracy of the Ubisense

system. However, the additional movement

characteristics perform much better, with

the walking speed providing the highest ac

curacy.