Intelligent elderly-care prototype for fall and disease detection

Inteligentni prototip za oskrbo starejših, ki zaznava padce in bolezni

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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.

Izvleček

Izhodišča: Delež starejših oseb, ki potrebujejo pomoč pri življenjskih opravilih, hitro raste. Vseh potreb starostnikov ne bo možno zadostiti z individualno oskrbo na domu ali institucionalnim varstvom. Analiza gibanja z inteligentnim sistemom je ena od možnosti, kako zagotoviti varnejše bivanje starostnikov doma. Komercialno dosegljivi sistemi že omogočajo enostavno zaznavanje padcev in varnostni nadzor, raziskave pa se ukvarjajo z naprednejšimi in bolj splošno uporabnimi rešitvami.

Metode: Na Institutu »Jožef Stefan« je bil pretežno v okviru projekta Confidence razvit prototip inteligentnega sistema, ki zbira in analizira podatke o običajnem gibanju ter nepredvidenih dogodkih in stanjih, kot so padci zaradi nezgode, varnostna ogroženost in nekatera bolezenska stanja. Za razliko od obstoječih enostavnih sistemov se uči in prilagaja posameznemu uporabniku. V članku so predstavljeni preizkusi z zdravimi prostovoljci, ki so igrali vloge normalnih gibalnih vzorcev in naučenih bolezenskih stanj ali nezgodnih dogodkov. Testirana je bila uporabnost različnih vrst senzorjev za spremljanje nadzorovane osebe: infrardeči senzorji, pospeškomeri in radiofrekvenčni senzorji.

Rezultati: Izvirno razvita programska oprema z veliko občutljivostjo in ločljivostjo se je izkazala za zanesljivo glede javljanja v primeru ogrožajočega dogodka in majhnega števila napak. S pomočjo senzorskega sistema Ubisense, ki zaznava položaje značk, pritrjenih na telo, je pravilno prepoznala 96 % padcev, kar je precej bolje od običajnejšega zaznavanja padcev z uporabo pospeškomerov. Poleg tega je prepoznala tudi do 99 % neobičajnih obnašanj.

Zaključki: Razviti prototip je pokazal, da inteligentni sistemi v kombinaciji z naprednimi senzorji postajajo vse sposobnejši in da lahko pričakujemo, da bodo v prihodnosti taki sistemi delovali kot pomočniki socialnih služb in zdravstvenih ustanov pri skrbi za starostnike. Sčasoma se bodo senzorji pocenili in takrat bodo takšni sistemi na trgu nadomestili trenutne manj zmogljive.

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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] According to the Administration on Aging, 19 % of people over 65 face limitations when performing the activities of daily living, and 4 % of them have severe disabilities.[3] The number 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] Intelligent 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 monitoring in order to be able to detect falls, dizziness, illness, unusual behavior due to dementia, 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 layers: 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 performance of the system because they determine what can be learned about the user's situation. Sensors differ in their accuracy, obtrusiveness and cost. An important group of sensors monitors the user's movement. Accelerometers measure accelerations, which can be used to detect the impact due to a fall, or the orientation of the body by measuring the direction of the Earth's gravity. Gyroscopes measure angular velocities and can also be used for fall detection. Both of these are typically worn on the waist or the chest, and they cost between €200 and €2,000. Indoor location sensors track the positions of tags that are attached to the body or clothes. An example is the Ubisense real-time locating system. It uses ultra-wideband radio signals to track tag positions, has an accuracy of 15 cm and costs around €10,000.[6] The Smart motion-capture system uses infrared cameras to track the positions of tags with an accuracy of 2 mm and costs around €100,000.[7]

Interpretation methods interpret the data from the sensors. They can be classified into three types, based on the time periods of the observation. The first type are short-term methods, measuring tens of seconds, which are used to recognize that the user has stood up, has opened a door, has fallen etc.[8] The second type are mid-term methods, measuring a few minutes or hours, and are used to recognize that the user is walking, has gone to the bathroom, is limping, etc. The last type are long-term methods, observing the whole day or several days, which are used to recognize the daily activities of the person and detect behavioral changes, such as staying in bed, not communicating with anybody for an unusually long time, or not going to lunch, which may be caused by physical or mental problems.

Services enable communication with caregivers, relatives, neighbors, doctors, and friends, and can be divided into three types. Intervention services act automatically in the case of dangerous events such as falls. Prevention services send informative messages about arising health problems, etc. Interaction services conduct the interaction between the system and the user and between the system and other entities, such as doctors, relatives, neighbors etc.

Related research on elderly-care systems

Related research can be divided into two categories. Some systems help the elderly perform daily tasks using home automation and user-friendly interfaces, but are only capable 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 performance on their own.

Soprano was a European 6th Framework 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, reminds the user about important tasks to be carried out, e.g., taking pills, etc. The MKS Electronic Systems collaborates in the project "Independent Residing enabled by Intelligent Solutions" (IRIS), which aims to enable 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, controlling 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 performing tasks such as water-leaks detection, video tracking of visitors, checking if the house is secured, and voice-controlled door locking 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 during falls.[8] The data were recorded by young subjects performing simulated falls. The data analysis showed that by defining an appropriate threshold, the accelerations during the falls and the accelerations produced during the normal activities of daily living can be distinguished. In similar publications, accelerometers with a simple threshold are often reported to achieve close to 100 % accuracy for typical falls. Perolle et al. described an elderly-care system that consists of a mobile module worn by the user, which is able to locate the user and detect falls.[12] The device 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.

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 typically implement simple functions such as opening doors on request or when a sensor detects proximity. In addition, they implement simple fall detection based on accelerometers. When tested in laboratory conditions and on straightforward cases of falls, the systems achieve a very high accuracy. However, they are usually not tested in complex 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 recognize 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 methods 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 Ethics Committee, approval 45–46/12/08. The three sets of tests reported here were conducted in experimental conditions at the Jožef Stefan Institute in a laboratory measuring 5×3 meters by healthy, young volunteers able to simulate falls and health problems as instructed by a physician. These tests included 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 persons—four male (24y, 24y, 31y, 26y) and one female (27y)—who imitated falls and four health problems: hemiplegia (hemipa-

Figure 1: Sensors – left: Smart tag, middle: Ubisense tag, right: accelerometer.

resis), pain in the leg, pain in the back and Parkinson's disease. These imitations were performed explicitly following typical clinical pictures as described in textbooks. Real patients may show less typical movement patterns, but in the initial experiments baseline 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 because 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 abnormally (25 with each of the four health problems) were recorded.

The second set of tests included 10 persons — six male (26y, 32y, 26y, 26y, 23y and 24y) and four female (27y, 26y, 33y and 28y)—who imitated falls. These recordings were captured with the Ubisense system 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 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 behavior (sitting down normally and quickly, lying 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 persons — 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 normal 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 connection. The Ubisense system can track tags within one apartment if the interior walls are not too thick or contain a lot of metal;

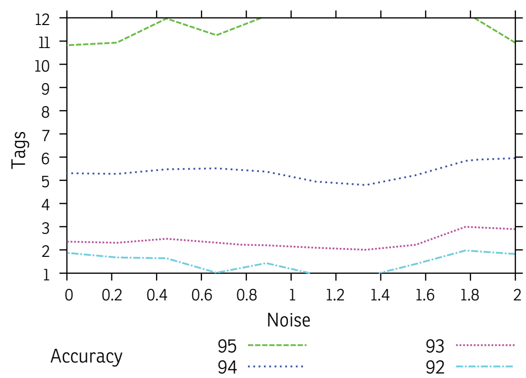

Figure 2: Accuracy of the short-term data analysis detecting falls.

however, the accuracy decreases in proportion to the number of obstacles.[17]

The data was processed by a novel intelligent real-time elderly-care prototype called Confidence, which was implemented at the Jožef Stefan Institute. This prototype represents the main achievement of the European 7th Framework Programme project Confidence.[18,19] It detects falls, recognizes unusual 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 Forest machine-learning classifier and expert knowledge in the form of rules.[20,21] Finally, the data are analyzed for all three observation periods.

The short-term data of a few seconds are used to recognize falls of several types: tripping, fainting, falling from the chair etc. The falls are recognized using expert rules (e.g., 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 general, the prototype collects statistics about the user's movement and builds a personalized model of usual behavior. If the user's behavior significantly deviates from the usual behavior, 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 Factor (LOF) algorithm.[24] The collected statistics characterize the user's gait (speed and length of a step etc.), turning (speed, angle etc.), walking speed, general speed of movement, 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 deterioration 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 portable 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 recognized, the prevention service informs the caregivers by sending the information on the usual and unusual behavior.

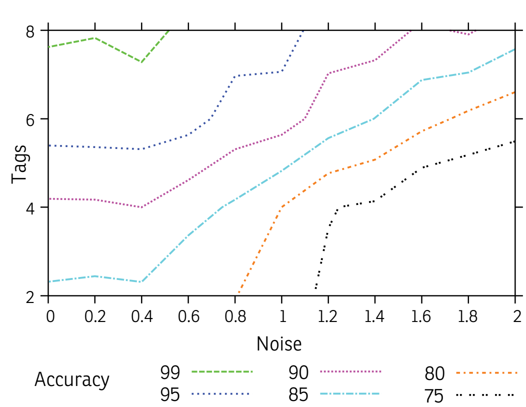

Figure 3: Accuracy of the mid-term data analysis recognizing unusual behavior in general.

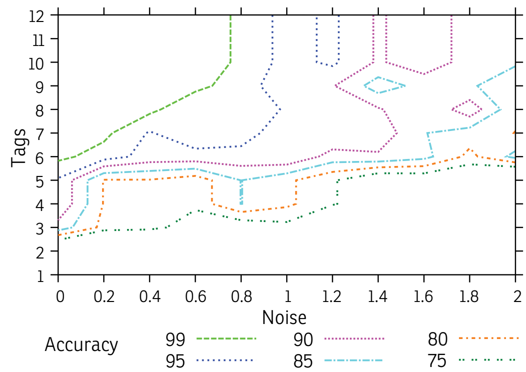

Figure 4: Accuracy of the mid-term data analysis recognizing specific health problems.

Results

The first set of tests of the Confidence prototype used the Smart sensor system with up to 12 body tags and varying degrees 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 degree of noise (horizontal axis). The curves in the figures represent the borders between the areas with different accuracies. The accuracies were measured with 10-fold cross-validation.

Figure 2 shows the accuracy of the short-term data analysis detecting falls. The number 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. Interestingly, the noise that was added to the data has an even smaller impact on the accuracy.

Figure 3 shows the accuracy of the mid-term data analysis recognizing unusual behavior, in general. This means that all the recordings of behavior with health problems 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 placements, 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 decreases 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 expected, 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 recognize falls. The results are presented in Table 1. They show that the prototype correctly distinguishes between falls and normal 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 Ubisense sensor system to recognize unusual

Table 1: Accuracies of recognizing falls and normal behavior.

Event	Fall/normal	Accuracy [%] using Ubisense	Accuracy [%] using accelerometer
Tripping	Fall	100.0	100.0
Fainting	Fall	98.0	10.6
Sliding from the chair	Fall	95.9	6.4
Lying down quickly	Normal behavior	100.0	34.0
Sitting down quickly	Normal behavior	100.0	96.8
Searching for something under a table/bed	Normal behavior	79.6	100.0
Overall		95.7	57.2

Table 2: Accuracies of recognizing normal and abnormal behavior.

Mid-term movement characteristics	Accuracy [%]
Gait	64.5
Turning	67.9
Walking speed	99.1
General speed	98.9
Posture transitions	98.6

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 accuracy.

Discussion

Europe is in dire need of high-performance reasonably priced AAL for the elderly. Research prototypes are beginning to achieve the performance needed to make a difference in the lives of the elderly, while the market still offers only limited solutions. The prototype described in this paper is one of the solutions providing an insight into the future of elderly-care systems.

The Smart and Ubisense sensor systems offer similar accuracies for fall detection. However, the Ubisense system probably outperformed the Smart system in testing because the experiments with the Smart system were performed first and by the time we started using Ubisense, the Confidence prototype had matured. The accuracy when using an accelerometer is significantly lower and is below the acceptable threshold. The only event that the accelerometer recognized more accurately than the Ubisense system was searching for something under a table/bed. This is because the accelerometer recognizes falls by detecting the impact with the ground, which was absent during this event, whereas the Ubisense system detects lying outside the bed, which this event resembled.

Regarding the detection of unusual behavior, the results show that with the Smart system using the same four tags as the Ubisense system, normal and unusual behavior can be distinguished with a 75 % to 90 % accuracy, depending on the degree of noise. This was accomplished by analyzing the gait characteristics only. With the Ubisense system, 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 post-processing, 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 recognizes falls and abnormal behavior. We tested three sensor systems: Smart, Ubisense and accelerometers. The results show that the Ubisense system is the most appropriate equipment for fall and unusual-behavior detection. Considering that the Ubisense system has a much lower price than the Smart system and is more practical, and at the same time achieved significantly better performance than the accelerometers, it seems to be the most appropriate of the three for high-quality fall detection in real life.

The performance achieved in laboratory tests surpassed the project's goals and the desired thresholds for real-life use. The only major problem, the cost of around €10,000, currently renders the prototype unsuitable for mass use, but with the rapid progress in electronics, it might take only a few years to achieve widespread adoption.

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