Lecture Notes in Electrical Engineering 725

Andrea Monteriù
Alessandro Freddi
Sauro Longhi *Editors*

Ambient Assisted Living

Italian Forum 2019

Springer

Lecture Notes in Electrical Engineering

Volume 725

The book series *Lecture Notes in Electrical Engineering* (LNEE) publishes the latest developments in Electrical Engineering - quickly, informally and in high quality. While original research reported in proceedings and monographs has traditionally formed the core of LNEE, we also encourage authors to submit books devoted to supporting student education and professional training in the various fields and applications areas of electrical engineering. The series cover classical and emerging topics concerning:

- Communication Engineering, Information Theory and Networks
- Electronics Engineering and Microelectronics
- Signal, Image and Speech Processing
- Wireless and Mobile Communication
- Circuits and Systems
- Energy Systems, Power Electronics and Electrical Machines
- Electro-optical Engineering
- Instrumentation Engineering
- Avionics Engineering
- Control Systems
- Internet-of-Things and Cybersecurity
- Biomedical Devices, MEMS and NEMS

For general information about this book series, comments or suggestions, please contact leontina.dicecco@springer.com.

To submit a proposal or request further information, please contact the Publishing Editor in your country:

China

Jasmine Dou, Editor (jasmine.dou@springer.com)

India, Japan, Rest of Asia

Swati Meherishi, Editorial Director (Swati.Meherishi@springer.com)

Southeast Asia, Australia, New Zealand

Ramesh Nath Premnath, Editor (ramesh.premnath@springernature.com)

USA, Canada:

Michael Luby, Senior Editor (michael.luby@springer.com)

All other Countries:

Leontina Di Cecco, Senior Editor (leontina.dicecco@springer.com)

**** This series is indexed by EI Compendex and Scopus databases. ****

More information about this series at http://www.springer.com/series/7818

Andrea Monteriù · Alessandro Freddi ·
Sauro Longhi
Editors

Ambient Assisted Living

Italian Forum 2019

Springer

Editors
Andrea Monteriù
Dipartimento di Ingegneria
dell'Informazione (DII)
Università Politecnica delle Marche
Ancona, Italy

Alessandro Freddi
Dipartimento di Ingegneria
dell'Informazione (DII)
Università Politecnica delle Marche
Ancona, Italy

Sauro Longhi
Dipartimento di Ingegneria
dell'Informazione (DII)
Università Politecnica delle Marche
Ancona, Italy

ISSN 1876-1100 ISSN 1876-1119 (electronic)
Lecture Notes in Electrical Engineering
ISBN 978-3-030-63106-2 ISBN 978-3-030-63107-9 (eBook)
https://doi.org/10.1007/978-3-030-63107-9

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Organization Committee

General Chair

Sauro Longhi, Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, Ancona

General Co-chair

Andrea Monteriù, Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, Ancona

Honorary Chair

Pietro Siciliano, Istituto per la Microelettronica e Microsistemi, Consiglio Nazionale delle Ricerche, Lecce

Scientific Committee

Alessandro Leone, Chair, Istituto per la Microelettronica e Microsistemi, Consiglio Nazionale delle Ricerche, Lecce
Bruno Andò, Dipartimento di Ingegneria Elettrica, Elettronica e Informatica, Università di Catania, Catania
Mario Alessandro Bochicchio, Dipartimento di Ingegneria dell'Innovazione, Università del Salento, Lecce
Marianna Capecci, Dipartimento di Medicina Sperimentale e Clinica, Università Politecnica delle Marche, Ancona

Niccolò Casiddu, Dipartimento Architettura e Design, Università degli Studi di Genova, Genova
Filippo Cavallo, Istituto di BioRobotica, Scuola Superiore Sant'Anna, Pisa
Maria Gabriella Ceravolo, Dipartimento di Medicina Sperimentale e Clinica, Università Politecnica delle Marche, Ancona
Amedeo Cesta, Istituto di Scienze e Tecnologie della Cognizione, Consiglio Nazionale delle Ricerche, Roma
Paolo Ciampolini, Dipartimento di Ingegneria e Architettura, Università di Parma, Parma
Gabriella Cortellessa, Istituto di Scienze e Tecnologie della Cognizione, Consiglio Nazionale delle Ricerche, Roma
Giovanni Diraco, Istituto per la Microelettronica e Microsistemi, Consiglio Nazionale delle Ricerche, Lecce
Leopoldina Fortunati, Dipartimento di Scienze Matematiche, Informatiche e Fisiche, Università di Udine, Udine
Luca Francioso, Istituto per la Microelettronica e Microsistemi, Consiglio Nazionale delle Ricerche, Lecce
Luciano Gamberini, Dipartimento di Psicologia Generale, Università degli Studi di Padova, Padova
Michele Germani, Dipartimento di Ingegneria Industriale e Scienze Matematiche, Università Politecnica delle Marche, Ancona
Massimiliano Malavasi, Centro Adattamento dell'Ambiente Domestico, Ausilioteca di Bologna, Bologna
Vincenzo Marletta, Dipartimento di Ingegneria Elettrica, Elettronica e Informatica, Università di Catania, Catania
Germano Paini, Dipartimento di Culture, Politica e Società, Università degli Studi di Torino, Torino
Massimo Pistoia, eResult S.r.l., Cesena
Claudia Porfirione, Dipartimento Architettura e Design, Università degli Studi di Genova, Genova
Gian Marco Revel, Dipartimento di Ingegneria Industriale e Scienze Matematiche, Università Politecnica delle Marche, Ancona
Lorenzo Scalise, Dipartimento di Ingegneria Industriale e Scienze Matematiche, Università Politecnica delle Marche, Ancona
David Scaradozzi, Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, Ancona
Federica Verdini, Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, Ancona

Organizing Committee

Lorena Rossi, Chair, Istituto Nazionale Riposo e Cura Anziani, Ancona
Irene Burroni, Cluster SMILE, Cluster Tecnologico Nazionale "Smart Living Technologies"
Laura Chies, Cluster SMILE, Cluster Tecnologico Nazionale "Smart Living Technologies"
Filippo D'Arpa, Cluster SMILE, Cluster Tecnologico Nazionale "Smart Living Technologies"
Assunta D'Innocenzo, AitAAL: Associazione Italiana Ambient Assisted Living
Luca Mion, Cluster SMILE, Cluster Tecnologico Nazionale "Smart Living Technologies"
Patrizia Sopranzi, Regione Marche

Local Committee

Alessandro Freddi, Chair, Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, Ancona
Sara Casaccia, Dipartimento di Ingegneria Industriale e Scienze Matematiche, Università Politecnica delle Marche, Ancona
Lucio Ciabattoni, Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, Ancona
Francesco Ferracuti, Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, Ancona
Sabrina Iarlori, Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, Ancona
Alessandro Mengarelli, Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, Ancona
Lucia Pepa, Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, Ancona
Mariorosario Prist, Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, Ancona
Luca Romeo, Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, Ancona

Preface

The tremendous progress that new technologies have had in the last decade, together with their significant reduction in cost, provided a formidable impetus to the development of increasingly flexible and customizable technological solutions to different user needs. This development had a particular impact on the progress of Ambient Assisted Living (AAL) technological solutions that aim to improving health, psycho-physical well-being, and the independent living of users with different needs or with disabilities. The result is that nowadays, AAL technologies are recognized by the European Commission as the enabling drivers to build the quality of life of our current and future society, to address the challenges of demographic changes, sustaining people in productive and healthy work, keeping people at home healthy, independent and integrated, and improving the delivery of care where and when needed.

All these aspects were explored and discussed during the Tenth Italian Forum on Ambient Assisted Living (ForItAAL), held in Ancona, Italy, in June 2019. The Italian Forum on AAL is one of the most important annual events for researchers, professionals, developers, policy-makers, producers, service providers, carriers, and end-user organizations working in the different fields of AAL, who present and disseminate results, skills, prototypes, products, and services. The book presents the refereed proceedings of the Forum and reviews the status of researches, technologies, and recent achievements on AAL. The coverage is wide ranging, with topical sections devoted to human monitoring, smart living services, biomedical and robotic solutions, including different case studies and real-world examples where AAL technologies are successfully applied. Using a multidisciplinary approach and different points of view, the book offers interesting insights, from research to practice, to all those directly or indirectly interested and involved in the field of AAL.

These insights will inspire the readers to continue their exploration of AAL technologies, promoting new technological solutions that will increasingly adapt to the user rather than the user adapting to these technologies.

Ancona, Italy

Andrea Monteriù
Alessandro Freddi
Sauro Longhi

Contents

Human Monitoring

Measuring Environmental Data and Physiological Parameters at Home to Assess the Caregiver Burden in Assistants of People with Dementia

Sara Casaccia, Andrea Calvaresi, Nicole Morresi, Lorenzo Scalise, Andrea Monteriù, Luca Romeo, Emanuele Frontoni, and Gian Marco Revel

Abstract Measuring the behaviour and health status of informal caregivers of people with dementia can predict the personal well-being of the caregivers. Informal caregivers struggle to remain active during the daily life activities avoiding the care burden. For this reason, in this work, an analysis of both the environmental data coming from PIR sensors, installed in the home environment, and physiological parameters, directly measured by the user, is performed to highlight, unusual behaviors that can increase the stress level of the caregiver. In addition, daily survey and personal interview provide further information about the progression of the illness and the amount of the care burden. Coupling this information with the physiological quantities can provide an overall health status of the caregiver. Results show that the caregiver presents a decreasing trend of her daily self-reported health status associated with a change in the pattern of the domotic data. The questionnaire also exhibits

S. Casaccia (✉) · A. Calvaresi · N. Morresi · L. Scalise · G. M. Revel
Dipartimento di Ingegneria Industriale e Scienze Matematiche, Università Politecnica delle Marche, via Brecce Bianche 12, Ancona, Italy
e-mail: s.casaccia@staff.univpm.it

A. Calvaresi
e-mail: a.calvaresi@pm.univpm.it

N. Morresi
e-mail: n.morresi@pm.univpm.it

L. Scalise
e-mail: l.scalise@staff.univpm.it

G. M. Revel
e-mail: gm.revel@staff.univpm.it

A. Monteriù · L. Romeo · E. Frontoni
Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, via Brecce Bianche 12, Ancona, Italy
e-mail: a.monteriu@univpm.it

L. Romeo
e-mail: l.romeo@staff.univpm.it

E. Frontoni
e-mail: e.frontoni@staff.univpm.it

A. Monteriù et al. (eds.), *Ambient Assisted Living*, Lecture Notes in Electrical Engineering 725, https://doi.org/10.1007/978-3-030-63107-9_1

a high correlation with body weight measurements (Pearson Coefficient of -86%) suggesting that the caregiver health status is limiting the normal daily activities, may be due to an increase of the care burden associated to a worsening of the illness.

1 Introduction

Behavioral and physiological measurements define the well-being, health and stress condition of caregivers [1]. Introducing Information and Communication Technology (ICT) solutions in the home environment can monitor the status of a patient for informal and formal caregivers that are outside the home [2] and the behavior and stress condition of the informal caregiver that lives with the patient. Sensor network are used to acquire data and signals of inhabitants and data processing can be performed to extract specific features as the care burnout. Several works indicated that caregivers of people with dementia are inclined to an increase of care burden [3]. The number of informal and formal caregivers of people with dementia are enormous and it is correlated with the number of people with dementia. The global number of people living with dementia was estimated at 43.8 million in 2016, an increase from 20 million in 1990. In 2050, this number is predicted to reach at 131.5 million [4]. This increase is coupled with a need of care which can results in care-related stress and burden among caregivers. Both professional and informal caregivers experience stress and repetitive negative emotions, not only at home, but also at work and outside [5]. The continuous demand and stress can result both in physical disease (e.g. cardiovascular, musculoskeletal) or mental disease (e.g. burnout, depression) [6], resulting in formal- and informal carers struggling to remain active during the daily life activities.

Most people with dementia live at home where they are dependent on informal caregivers for their daily care. In particular, female, spousal caregivers appear to be at risk of depression, anxiety and caregiver burden [6]. To decrease the negative influence of such critical home condition, measurements of the environment and health status may identify the decline of the caregiver well-being. At the same time understanding the factors that influence the caregivers' health state is fundamental for the development of effective support [7].

This paper is focused on an accurate analysis of the data and signals measured on an informal caregiver that lives with a person with dementia to identify changes in the behavior, physiological parameters and mental conditions. To measure the personal well-being of the caregiver, data provided by different Passive InfraRed (PIR) sensors installed in the home environment are investigated and they are associated to the physiological parameters acquired by the user three times a week for a year. A validation period of two months is performed using a daily survey and monthly interview to the user to study a correlation between the physiological parameters' trend and the behavior of the caregiver as the care burden increases with the worsening of the dementia.

2 Methodology

This paper aims at identifying the burden of a caregiver which lives and takes care of a person with dementia by measuring the behavioral change in the home environment and correlating it with the increasing burnout of the caregiver.

To monitor the personal condition of the caretaker, three main physiological quantities such as mean arterial pressure (MAP), heart rate (HR) and body weight (W) are acquired. Sensors' characteristics are reported in Table 1.

These devices are selected by the authors since a combination of the measured variables can be representative of the overall valuation of the general health status of the monitored user. In addition, these devices can be easily adopted by older people as they are widely spread among the daily routine of the user.

For this particular analysis, a family was chosen from a bigger pilot case that includes 8 apartments and 13 older users in a town in Italy [8]. This work is part of the Italian Smart Cities project "Health@Home: Smart Communities for citizens' wellness" (H@H).

The selected family is characterized from a couple of married people. The man (77 years old) is affected from dementia at the mid-stage. His wife is 71 years old and she is in a good health condition, not presenting any severe pathology. Every day from Monday to Friday, she brings him to the daily center for people with dementia at 9 am and she brings her husband back home at 4 pm. In the evening, during the night and weekends, she takes care of her husband alone in the home environment.

2.1 Monitored Parameters

The physiological parameters considered for the study are the body weight, heart rate and blood pressure. The physiological data are collected using a tablet with a customized User Interface (see Fig. 1).

The system architecture, data connection and Cloud database are described in [8–10].

Table 1 Technical specifications of the devices used by the caregiver for the physiological measurements

Device	Description	Accuracy	Resolution	Range
Taidoc TD3128B	Blood pressure meter to monitor diastolic, mean and systolic blood pressure and HR	Systolic: ±3 mmHg (±2%) Diastolic: ± 3 mmHg (±2%) HR: ±4%	1 mmHg (systolic, diastolic) 1 bpm (HR)	Systolic: 60–255 mmHg Diastolic: 30–195 mmHg HR: 40–199 bpm
Taidoc TD2555B	Body weight scale	±0.3 kg (±0.5%)	0.1 kg	4–250 kg

Fig. 1 The customized user interface for data collection, a blood pressure meter to monitor the blood pressure and heart rate and a body weight balance to acquire the body weight

The dataset is characterized from behavioral data coming from domotic sensors installed in the domestic environment and physiological signals collected during the daily measurements [11].

For what concern the behavior analysis, the data comprised of the signal outputs of three PIR sensors, installed in the living room, bedroom and bathroom (see Fig. 2).

2.2 Questionnaires Data

The questionnaire is divided in two parts.

The first part is a daily survey based on the SF36 and SF12 questionnaires [12, 13] and related to the physical activity and condition of the caregiver which filled the questionnaire every day for two months before going to sleep. For this specific analysis, one question, representing the global health condition of the caregiver is analyzed. The question is:

1. Did your health limit you in your daily routine?

The user can answer the question with 1 (representing that the user has been totally limited in doing daily activities from its health), 2 (the user can do its own activity but in a limited way) or 3 (the health status does not affect its health at all).

Fig. 2 Plan of the apartment and location of the 3 PIR sensors (placed in the living room, bathroom and the bedroom, respectively)

The raw survey is processed using a moving average technique that creates a series of averages of different subsets of the full dataset as described in [14]. This technique provides a trend in the person's behavior and aims at forecasting the well-being changing over time.

The second part of the questionnaire consists on a face-to-face interview made once a month for two months from an external assistant. The interview aims to investigate both mental and physical status of the caregiver and in turn, the caregiver gave an update of the disease status of the person with dementia.

2.3 Data Analysis

The information extracted from PIR sensors indicates whether the user has entered the room and/or is moving within the room. Therefore, data are processed by counting the number of occurrences of the sensor switch-on. In particular, PIR activations are hourly counted and then processed by aggregating the total number of activations recorded in a time interval of one hours. Then hourly aggregation is grouped together in 4 time intervals of 6 consecutive hours that represents: night (0–6), morning (7–12), afternoon (13–18) and evening (19–24).

The methodology has been applied considering a validation period of two months in which data are processed to evaluate if there are some differences in the behavior of the family unit. The discrepancy between the two months are evaluated on the basis of the total activation of the PIR for a specific time frame respect to the number of the activation of the overall two months period according to the following equation:

$$\%Activation_{m_i} = \frac{\sum Activation_{m_i}}{\left(\sum Activation_{m_i} + \sum Activation_{m_k}\right)} \tag{1}$$

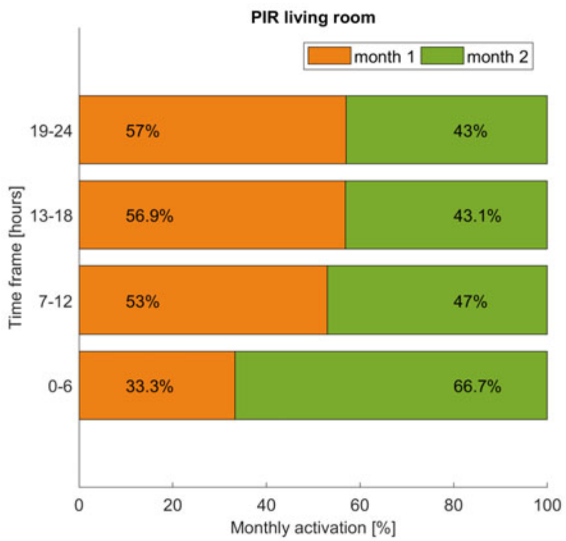
where m_i refers to the i-th month while m_k is the k-th month. The numerator is the number of total activations of the selected sensor occurred in a single month and the denominator represents the total number of activations during the two months period.

3 Results

In this section, some observations and results are presented. Data analysis provides the number of the total activations of the PIR sensors in the different time frame of the day for each month. Therefore, the variation of this quantities is analyzed.

Figures 3, 4 and 5 show the percentage of activation of each PIR (installed in the living room, bedroom and bathroom) for the two months over each daily period. In particular, the attention is focused on the PIR installed in the living room and bathroom. The activations of these sensors in month 2 are higher than in month 1

Fig. 3 Percentage of activation of the PIR installed in the living room through different time frame of the day, for the 2 months monitored for the validation phase



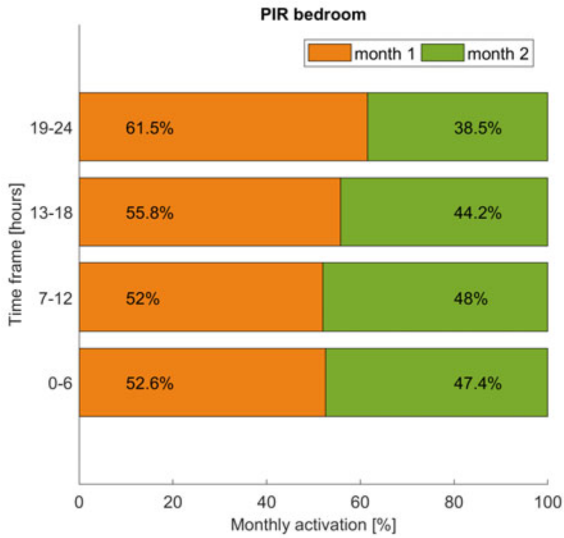


Fig. 4 Percentage of activation of the PIR installed in the bedroom through different time frame of the day, for the 2 months monitored for the validation phase

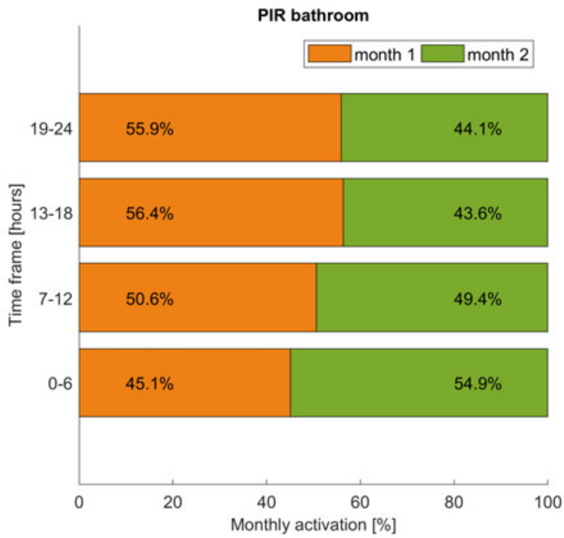


Fig. 5 Percentage of activation of the PIR installed in the bathroom through different time frame of the day, for the 2 months monitored for the validation phase

for the time slot 0–6. These results show how the family changed their nocturnal behavior.

In particular, the increasing of the activities in the living room and bathroom can be associated with a worsening of the dementia disease. This result is in line with medical findings in the scientific literature which highlights how the changes in the sleep patterns can be associated with the illness drop [13].

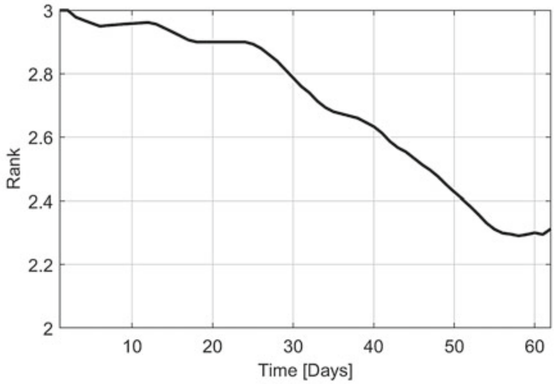


Fig. 6 Trend of the daily survey provided by the caregiver across the two months of validation period

On the other hand, observing the time frames 7–12, 13–18 and 19–24 it is possible to note that the activations number decrease: a possible explanation is that in these specific time frames the house is only occupied by the caregiver since the dementia patient is supposed to be at the health center. Moreover, during the interviews she declares a repeated back pain that limits her daily routine.

The second observation is focused on the daily survey and monthly interviews.

Figure 6 shows the trend of the daily survey provided by the caregiver, processed with a moving average technique, for the 2 months of validation period. A decrease of the rank from 3 to 2 denotes that the caregiver perception of her personal health condition is lower in month 2 than in month 1. This can be associated with the higher nocturnal activity of the family in month 2. The decrease of the self-reported health status is also correlated with the self-reported interview: the caregiver reported an increased repeated back pain events during the second month.

In particular, from the monthly interviews, the authors extracted that the caregiver is more stressed in month 2 than in month 1 caused from a back pain and a worsening of her husband's conditions.

The last observation is related to the correlation of the processed daily survey with the physiological parameters monitored 3 times a week from the caregiver using the blood pressure meter and the body weight scale. Table 2 reports the results of the Pearson's coefficient that indicates the existing correlation from the physiological parameters (e.g. heart rate, mean blood pressure and body weight) and the daily survey processed with the moving average technique.

Table 2 Pearson correlation coefficient standardized from 0 to 100% computed between the survey provided during the validation period and the physiological parameters measured by the caregiver

Parameter	Mean arterial pressure	Heart rate	Weight
Pearson coefficient (%)	39	−46*	−86*

*p-val < 0.05

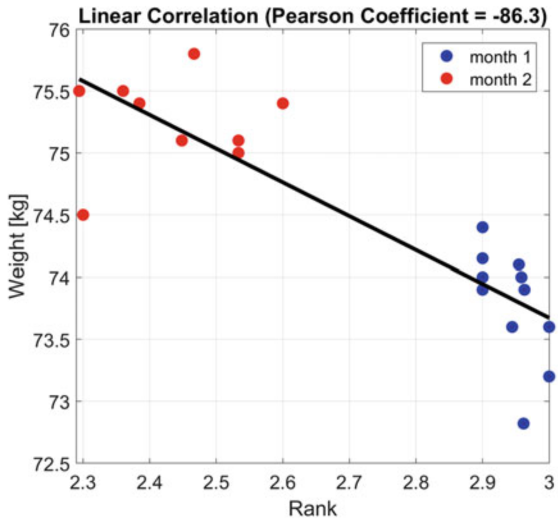


Fig. 7 Plot of the linear correlation between the weight measured by the caregiver and the respective self-reported health status provided in the survey. Note that there is a decreasing trend of the weight as the caregiver rank its day with a higher vote

To test the meaningfulness of the data, P-value (p) was set at 0.05 (significance level). When $p < 0.05$, the correlation between the data and the survey is statistically significant [15]. Table 2 highlights that the survey correlates most with the body weight ($R = -86\%$) of the caregiver.

Figure 7 suggests that an increase in the body weight is strictly connected with a decrease in the questionnaire rank (i.e., a decrease of the self-reported health status) which means that the caregiver health status is limiting the normal daily activities causing a more inactive and steady condition. The decrease of the caregiver health status may be due to an increase of the care burden correlated with the worsening of the patient's dementia state.

4 Conclusions

In this work, a heterogeneous sensor network installed in the home environment is used to monitor the behavior of a family (a person with dementia and his wife) and the health status of the informal caregiver to identify the caregiver burden together with questionnaires and interviews. In this paper, the authors process environmental data and physiological signals to understand the stress and health condition of the informal caregiver associated with the worsening of the dementia of the patient at home. In particular, domotic quantities acquired from PIR sensors installed in the home environment were monitored: the analysis shows an increasing nocturnal activity in the period 0–6 for month 2 of the validation period.

This condition can be associated with the degeneration of the illness of the patient, which results in a discontinuous sleep pattern that causes extended awake phases during the night. For this reason, the caregiver presents an increasing level of personal stress confirmed by the daily survey and the monthly interview. In fact, there is a decreasing trend in the rank of the questionnaire that accentuate the decaying status of the health and an increasing care burden. Moreover, the interview reports how the caregiver itself is affected by some back pain due to the advanced age that contributes both to the limitation in the daily activities' routine and a major effort for taking care of the dementia patient.

More in detail, studying the correlation between the biomedical data and the questionnaire during the validation period, it is possible to observe that a decrease in the caregiver's self-reported health status representing a higher limitation in the daily activity of the caregiver is strictly connected with an increase of the body weight. The correlation between the daily survey and the body weight shows a Pearson coefficient of -86%. A possible explanation is the limited amount of the daily activity performed by the caregiver due to the caregiver health status and to the repeated stress condition associated with the caregiver's task.

This consideration comes from an accurate analysis provided by the association of multiple quantities which are domotic data, physiological data and information provided by the caregiver. Therefore, weight measurements can be interpreted as a partial index of the caregiver health status that as to be linked to the progress of illness. In conclusion, this paper shows that with a heterogeneous sensor network installed in the home environment is possible to extract the behavior and health status of people inside the home and evaluate the behavioral variations in different period of time. The aggregation between environmental data, physiological parameters and questionnaire provides relevant information to identify the caregiver burden.

Future works will be focused on increasing the number of participants to the experimentation to test the methodology and improve the statistical analysis. Patients at different stages of dementia and their caregivers could be included in the study and a longer period of daily report could improve the results.

Acknowledgements The authors thank the project partners from Università La Sapienza and Università degli Studi di Genova and we gratefully acknowledge support from the Italian Ministry of Education, University and Research (under grant no. SCN_00558—Italian Smart-Cities Project "Health@Home").

References

1. Visser-Meily JMA, Post MWM, Riphagen II, Lindeman E (2004) Measures used to assess burden among caregivers of stroke patients: a review. Clin Rehabil 18:601–623. https://doi.org/10.1191/0269215504cr776oa
2. Mitabe N, Shinomiya N (2016) Support system for caregivers with sensor network and machine learning. In: 2016 IEEE 5th global conference on consumer electronics, pp 1–4
3. Black W, Almeida OP (2004) A systematic review of the association between the behavioral and psychological symptoms of dementia and burden of care. Int Psychogeriatr 16:295–315. https://doi.org/10.1017/S1041610204000468

4. Launer LJ (2019) Statistics on the burden of dementia: need for stronger data. Lancet Neurol 18:25–27. https://doi.org/10.1016/S1474-4422(18)30456-3
5. Hategan A, Bourgeois JA, Cheng T, Young J (2018) Caregiver burnout. In: Hategan A, Bourgeois JA, Cheng T, Young J (eds) Geriatric psychiatry study guide: mastering the competencies. Springer International Publishing, Cham, pp 433–442
6. Jütten LH, Mark RE, Sitskoorn MM (2019) Empathy in informal dementia caregivers and its relationship with depression, anxiety, and burden. Int J Clin Health Psychol 19:12–21. https://doi.org/10.1016/j.ijchp.2018.07.004
7. Quinn C, Nelis SM, Martyr A et al (2019) Influence of positive and negative dimensions of dementia caregiving on caregiver well-being and satisfaction with life: findings from the IDEAL study. Am J Geriatr Psychiatry. https://doi.org/10.1016/j.jagp.2019.02.005
8. Casaccia S, Pietroni F, Scalise L et al (2018) Health@Home: pilot cases and preliminary results: integrated residential sensor network to promote the active aging of real users. In: 2018 IEEE international symposium on medical measurements and applications (MeMeA), pp 1–6
9. Monteriù A, Prist MR, Frontoni E et al (2018) A smart sensing architecture for domestic monitoring: methodological approach and experimental validation. Sensors 18:2310. https://doi.org/10.3390/s18072310
10. Scalise L, Pietroni F, Casaccia S et al (2016) Implementation of an "at-home" e-Health system using heterogeneous devices. In: 2016 IEEE international smart cities conference (ISC2), pp 1–4
11. Pietroni F, Casaccia S, Revel GM et al (2019) Smart monitoring of user and home environment: the Health@Home acquisition framework. In: Casiddu N, Porfirione C, Monteriù A, Cavallo F (eds) Ambient assisted living. Springer International Publishing, pp 23–37
12. Hurst NP, Ruta DA, Kind P (1998) Comparison of the MOS short form-12 (SF12) health status questionnaire with the SF36 in patients with rheumatoid arthritis. Br J Rheumatol 37:862–869
13. Mallinson S (2002) Listening to respondents: a qualitative assessment of the short-form 36 health status questionnaire. Soc Sci Med 54:11–21
14. Elbayoudi A, Lotfi A, Langensiepen C (2019) The human behaviour indicator: a measure of behavioural evolution. Expert Syst Appl 118:493–505. https://doi.org/10.1016/j.eswa.2018.10.022
15. Lee H-A, Lee H-J, Moon J-H et al (2017) Comparison of wearable activity tracker with actigraphy for sleep evaluation and circadian rest-activity rhythm measurement in healthy young adults. Psychiatry Investig 14:179–185. https://doi.org/10.4306/pi.2017.14.2.179

A Vision-Based Approach for the at Home Assessment of Postural Stability in Parkinson's Disease

Claudia Ferraris, Roberto Nerino, Antonio Chimienti, Lorenzo Priano, and Alessandro Mauro

Abstract Postural instability is one of the main burdens of Parkinson's Disease as it increases the risk of falls and injuries. Monitoring any changes in postural stability, as a consequence of therapies and disease progression, is therefore highly desirable to preserve people's safety and quality of life. In this context, we present a vision-based system built around an optical RGB-Depth device for the automatic evaluation and home monitoring of postural stability. The system is able to track and evaluate body movements, and can be self-managed by people with impairment through an easy-to-use human–machine interaction. A set of static and dynamic balance tasks are delivered and analyzed by the system to estimate some postural and temporal parameters used for the objective and automatic assessment of postural stability. Compliance between automatic and clinical assessment is supported by a machine learning approach with supervised classifiers. Preliminary results of the study are presented and discussed.

C. Ferraris (✉) · R. Nerino · A. Chimienti
IEIIT-CNR, Corso Duca degli Abruzzi 24, Turin, Italy
e-mail: claudia.ferraris@ieiit.cnr.it

R. Nerino
e-mail: roberto.nerino@ieiit.cnr.it

A. Chimienti
e-mail: antonio.chimienti@ieiit.cnr.it

L. Priano · A. Mauro
Department of Neurosciences, University of Turin, Via Cherasco 15, Turin, Italy
e-mail: lorenzo.priano@unito.it

A. Mauro
e-mail: alessandro.mauro@unito.it

A. Monteriù et al. (eds.), *Ambient Assisted Living*, Lecture Notes in Electrical Engineering 725, https://doi.org/10.1007/978-3-030-63107-9_2

1 Introduction

The alteration of postural stability is one of the symptoms in Parkinson's Disease (PD) which negatively affects the people's safety and quality of life, as it increases the risk of falls and injuries [1], and worsens with the disease progression causing a significant cost for the healthcare system [2].

Several clinical scales are available to assess the postural stability and balance dysfunctions: Time Up and Go (TUG) test [3]; Postural Instability and Gait Difficulty (PIGD) [4], a sub-score of Unified Parkinson's Disease Rating Scale (UPDRS) [5]; Berg scale [6]. The combination of multiple balance tests [7] and the execution of concurrent cognitive or secondary motor tasks in steady standing conditions [8] can provide a better assessment of postural stability in PD than each scale separately.

Recent studies on standing stance [9] and dopaminergic treatments [10] in PD have shown the strong correlation between balance dysfunctions and postural sway, which refers to the continuous movement of the Center of body Mass (CoM) activated to maintain balance. Therefore, frequent monitoring of postural sway is desirable to control alterations of stability that could cause the subject to fall.

Recently, several non-contact approaches to body movement analysis based on low-cost optical tracking devices [11] have been successfully proposed as non-invasive alternatives to on-body inertial sensors [10] in different applications. In PD and other neurological diseases, non-contact approaches have been employed for the evaluation of Time Up and Go test [12], automatic classification of gait patterns and disorders [13], and objective assessment of UPDRS tasks [14].

Considering both the importance in PD of evaluating postural stability frequently as a predictor of the risk of falls and the advantages of several balance scales and concurrent tasks, it is desirable to develop solutions for the characterization of postural stability through the analysis of body movements in multiple dedicated tasks.

Along this line of research, a vision-based system has been developed for the automated assessment of postural stability at home. The system captures and analyzes the subject's body movements while performing specific tasks designed from standard balance scales. The aim is to emphasize balance dysfunctions by concurrent cognitive tasks (dual-task condition) and multiple balance tests, this to produce different types of postural stress and provide a more complete assessment [7]. The quantitative evaluation of postural stability is based on objective parameters estimated from CoM movements. A machine learning approach with supervised classifiers is used to automatically evaluate postural stability through postural and temporal parameters correlated with standard clinical evaluations. Preliminary results on the effectiveness and accuracy of the system, compared with clinical assessments, are presented and discussed.

2 Framework Description

2.1 System Description

The acquisition system has been designed to be low-cost, based on non-contact measurements and suitable for home monitoring: particular attention was paid to Human–Machine Interaction (HMI) to make it easily manageable without technical skills.

2.1.1 System Hardware, Software and Human–machine Interaction

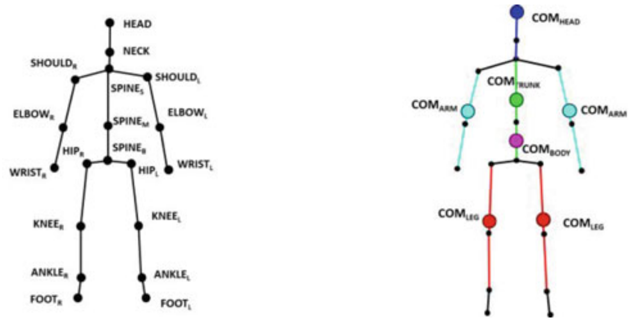
The developed solution is a vision-based system built around an RGB-Depth camera. As part of a broader implemented solution for the remote monitoring of PD subjects, the setup makes use of Microsoft Kinect v.2, a long-range camera that provides synchronized color and depth streams at 30 FPS. The camera is connected to a mini-PC (i.e., Intel® NUC i7) via a USB port. A monitor is used to display the Graphical User Interface (GUI) to provide visual information and feedback to the user (Fig. 1a).

The software running on mini-PC consists of dedicated C++ and MATLAB routines to access and analyze the information provided by the Software Development Kit (SDK) of the camera, in particular video streams and skeletal model. The acquisition and data processing of the skeletal model in real-time are crucial to ensure a reliable human–machine interaction based on simple gestures or actions such as positioning, raising or moving some parts of the body (Fig. 1b).

Each GUI consists of interactive objects and implements an augmented reality (AR) environment in which the user see her/his movements by a real-time visual feedback. In addition, the interactive objects are arranged to limit the movements required and are customizable to ensure good visibility. Finally, each GUI uses text messages, video and audio to suggest the steps required to complete the test session.

(a) Acquisition system (b) GUI with interactive object

Fig. 1 **a** The vision-based system consisting of RGB-Depth camera, mini-PC and monitor. **b** Example of GUI with interactive objects to perform selections



(a) Skeletal model with joints position (b) COM_{Body} position

Fig. 2 **a** Skeletal model and joints positions (joints related to hand and fingers are not represented). **b** Example of CoM_{Body} position (magenta) with the position of CoM of body segments used for Eq. 1

2.1.2 Body Center of Mass Estimation

The skeletal model consists of 25 three-dimensional joins (Fig. 2a) that follow the real-time body movements. The 3D coordinates of the joints are resampled at 30 Hz and filtered with a second order low pass Butterworth filter (cut-off 8 Hz) to remove high frequency noise. The Center of Mass of the body (CoM_{Body}) is calculated as a weighted average (Eq. 1) of the center of mass (CoM_i) of six body segments (namely head, arms, trunk and legs), as in [14].

$$\mathbf{CoM}_{\mathrm{Body}} = \frac{1}{6}\sum_{i=1}^{6} \mathbf{CoM}_{\mathrm{i}} * \mathrm{w_i} \tag{1}$$

CoM_i are evaluated from the joints of the skeleton model; weights (w_i) are set from anthropometric tables [15]: Head = 0.081 (w_1); Total Arm = 0.05 (w_2,w_3); Trunk = 0.497 (w_4); Total Leg = 0.161 (w_5,w_6). An example of CoM_{Body} position is shown in Fig. 2b. Note that CoM_{Body} is a 3D point since it is estimated from 3D joints.

2.2 Participants

Ten PD subjects were recruited, according the UK Parkinson's Disease Society Brain Bank Clinical Diagnostic standards [16], with no history of neurosurgical procedures, previous injuries to lower limbs, excessive tremor (severity <= 1) or cognitive impairment (Mini–Mental State Examination Score >= 27/30). An expert neurologist assessed the subjects' scores for the Berg scale, the TUG test and the PIGD score, defined as the sum of four UPDRS tasks namely: arising from chair, gait, posture and postural stability. Subjects characteristics were: Hoehn and Yahr score (average 2.4, min 1, max 3); PIGD score (average 8.2, min 3, max 12); Berg score (average 53.8, min 52, max 56); TUG time (average 10.2, min 9.7, max 14.3); age 54–75 years; disease duration 3–9 years. An age-matched control group (CG) of 10 volunteers was created: the exclusion criteria were previous falls and any neurological, motor or cognitive disorders. All participants subscribed informed consent according to the Declaration of Helsinki (2008). They were initially instructed by technicians on the use of the system in a laboratory environment, then they used the system autonomously via the HMI. CG subjects performed the same set of tasks under the same operative conditions of the PD subjects.

2.3 Experimental Procedure and Data Acquisition

Each test session consists of the following tasks, built on standard scales for the assessment of balance dysfunctions: Up-Stand-Down (USD), Tandem-Standing (TS), Reaching-Standing (RS), One-Leg-Standing (OLS) and Time-Up-and-Go (TUG). During the USD task, the subject has to get up from a chair, stand without support for 1 min and sit down; in the TS one, she/he has to stand for 1 min with feet spaced one step ahead; in RS one, she/he has to stand for 1 min with arms outstretched; in OLS one, she/he has to stand for 10 s on the dominant leg; while in the TUG one, she/he has to get up from a chair, walk 3 m, return to the chair and sit down.

The USD, TS, RS and OLS tasks are designed directly from the Berg balance scale. To ensure safety at home without supervision, only few of the Berg scale tests were considered, excluding those requiring closed eyes, rapid body movements or rotations. The TUG task is the standard 3-m long walk. All tasks are performed with open eyes. In the USD (Fig. 3), TS and RS tasks, the 1-min phase is divided into two

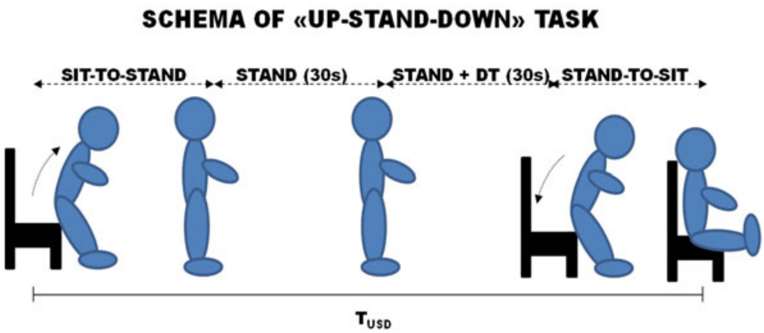


Fig. 3 Schema of the USD task: Sit-To-Stand, Stand for 30 s (ST), Stand for 30 s (DT), Stand-To-Sit. T_{USD} is the total time to complete the task