ORIGINAL RESEARCH

Experimenting quality of life telemonitoring in a real scenario

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Abstract

In the last decades, the worldwide growth and adoption of eHealth solutions has impacted life expectancy and improved quality of life, especially of people living in developed countries. One key common feature of all those novel eHealth solutions is telemonitoring, which makes possible to remotely assess health status and quality of life of individuals. Telemonitoring systems usually acquire heterogeneous data coming from sensors (physiological, biometric, environmental; wearable, non-invasive, adaptive and transparent to user) and other sources (*e.g.*, interaction with the user through digital services). By analyzing those data, systems become aware of user context and are able to automatically infer user's behavior as well as detect anomalies. In that way, they provide elaborated and smart knowledge to clinicians, therapists, carers, families, and the patients themselves. In this paper, we present a solution aimed at automatically assessing quality of life of people. The goal is twofold: to provide support to people in need of assistance and to inform therapists, carers and families about the improvement/worsening of quality of life of monitored people. The paper presents first experiments that have been performed in Barcelona to automatically assess MOBILITY, SLEEPING and MOOD of a body-abled user. Since results show that the approach is effective in that scenario, the system has been then installed and it is currently running at three homes of people with severe disabilities.

Key Words: Quality of life, Telemonitoring, Context-awareness, Sensor-based systems, Machine learning, eHealth

1 Introduction

People that need assistance, as for instance elderly or disabled people, may be affected by a decline in daily functioning that usually involves the reduction and discontinuity in activities of daily living and a worsening of the overall quality of life (QoL). In fact, this decline usually implies a change of habits and behavior of the people involved; for instance, quality of sleep may become worse together with a decrease of mobility, affecting and worsening the overall mood.

In the literature, several QoL scales and questionnaires to measure QoL have been proposed. Answered and compiled questionnaires are then analyzed by therapists and medical doctors in order to figure out the evolution of the quality of life of their patients. Among others, let us recall here the WHOQOL-BREF questionnaire,[1] which comprises 26 items to measure the corresponding physical health, psychological health, social relationships, and environment factors; the EQ-5D-5L questionnaire,[2] which provides a simple descriptive profile and a single value for health status that can be used in the clinical and economic evaluation of healthcare as well as in population health surveys; the RAND-36 questionnaire,[3] which is comprised of 36 items that assess eight health concepts (including physical functioning, role limitations caused by physical health problems, role limitations caused by emotional problems, social functioning, emotional well-being, energy/fatigue, pain, and general

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health perceptions); the Short Form (36) Health Survey (SF-36v2),[4] a questionnaire about patient health status which is commonly used in health economics for the quality-adjusted life year calculation to determine the cost-effectiveness of a health treatment; and the Barthel scale,[5] which is used to measure performance in Activities of Daily Living (ADLs).

It is worth noting that answers given to questionnaires are completely subjective depending on the patient behavior and attitude (*e.g.*, optimistic versus pessimistic), her/his status (*e.g.*, people with mobility impairment versus able-bodied people), and her/his perception of life (*e.g.*, young people versus elderly people). In spite of their intrinsic subjectivity, they are commonly used by therapists and medical doctors in order to monitor QoL trends in people at risk of decline in daily functioning. Unfortunately, answering questionnaires often becomes tedious and annoying for users or, even worse, impossible in cases of severe impairment.[6] Hence, intelligent and autonomous solutions need to be investigated.

In Ref.,[7] we presented a generic methodology aimed at automatically assessing QoL of people by relying on context-aware techniques. This paper advances that work presenting the results of the system in assessing three QoL items: MOBILITY, SLEEPING, and MOOD. The adopted solution is based on a sensor-based telemonitoring system. Data gathered from the home sensors and outdoor data collected by the smartphone are continuously processed and analyzed through machine learning techniques and suitable classifiers built to recognize the score perceived by the user on the selected QoL item. The system has been firstly evaluated with an able-bodied user (female, 41-years-old) for a period of 3 months and performance in terms of F1 measure shows the effectiveness of the approach. Results concerning this first evaluation are presented here. Subsequently, under the umbrella of the EU project BackHome (`http://www.backhome-fp7.eu/`), the system has been installed for testing in three disabled users' real homes.[8]

2 Method

The proposed methodology relies on a sensor-based telemonitoring system to monitor people indoors and outdoors. In fact, gathered data are used to study activities and habits of the monitored users considering a set of relevant automatically-extracted features. Those features are then used to automatically assess QoL of monitored users.

In Ref.,[7] we defined a Visual Analogic Scale (VAS) QoL questionnaire composed of the following items: MOOD, HEALTH, MOBILITY, SATISFACTION WITH CARE, USUAL ACTIVITIES (which includes SLEEPING), and PAIN/DISCOMFORT. Those items have been categorized in two families: monitorable and inferable. Monitorable items can be directly gathered from sensors without relying on direct input from the user. Inferable items can be assessed by analyzing data retrieved by the system when considering activities performed by the user not directly linked with the sensors. In this paper, we focus on two monitorable items (*i.e.*, MOBILITY and SLEEPING) and one inferable (*i.e.*, MOOD). In particular, the system is able to detect and acknowledge the location of the user over time as well as the covered distance in kilometers and the places where s/he stayed. At the same time, the system detects when the user is sleeping as well as how many times s/he is waking up during the night. Merging and fusing the information related to MOBILITY and SLEEPING, we are also inferring the overall MOOD.

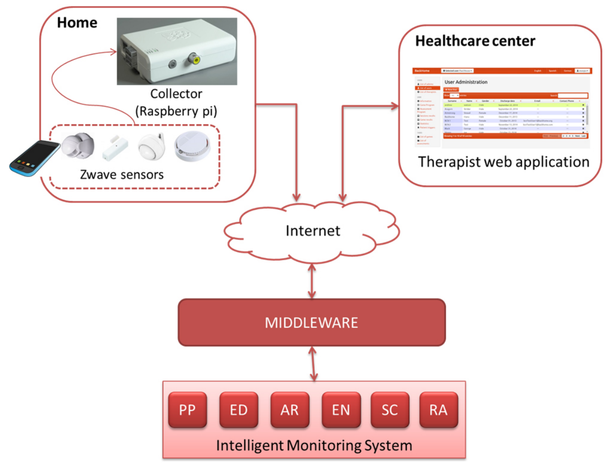

Figure 1: Main components of the adopted sensor-based system

2.1 The sensor-based system

In Figure 1, the high-level architecture of the adopted sensor-based system is sketched. The full architecture of our system is described in Ref.[9] As shown, its main components are: home; middleware; intelligent monitoring system; and healthcare center.

At home, a set of sensors are installed: presence sensors (*i.e.*, Everspring SP103), to identify the room where the user is located (one sensor for each monitored room); a door sensor (*i.e.*, Vision ZD 2012), to detect when the user enters or exits the premises; electrical power meters and switches, to control leisure activities (*e.g.*, television and pc); and pressure mats (*i.e.*, bed and seat sensors) to measure the time spent in bed and wheelchair. The system is also composed of a network of environmental sensors that measures and monitors environmental variables like temperature and humidity, but also potentially dangerous events like gas leak, fire, CO escape and presence of intruders. All the adopted sensors are wireless z-wave. They send the retrieved data to a collector (based on Raspberry pi). The Raspberry pi collects all the retrieved data and securely redirects them to the cloud where they are stored, processed, mined, and analyzed. We are also using the user's smartphone as a sensor by relying on Moves (`http://www.moves-app.com/`), an app for smartphones able to recognize physical activities and movements by transportation.

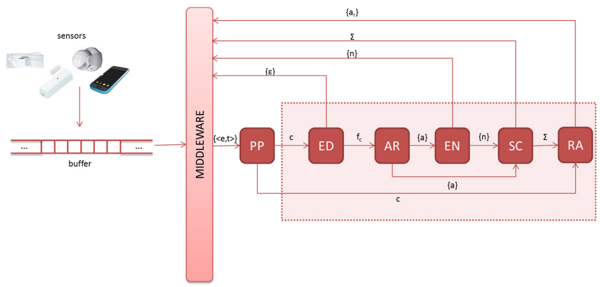

Figure 2: The Intelligent Monitoring system

The middleware, which acts as a SaaS, is composed by a secure communication and authentication module; API module to enable the collector to transmit all the data from sensors and to make them available to the activity monitoring module; and further utilities such as load balancing and concurrency.

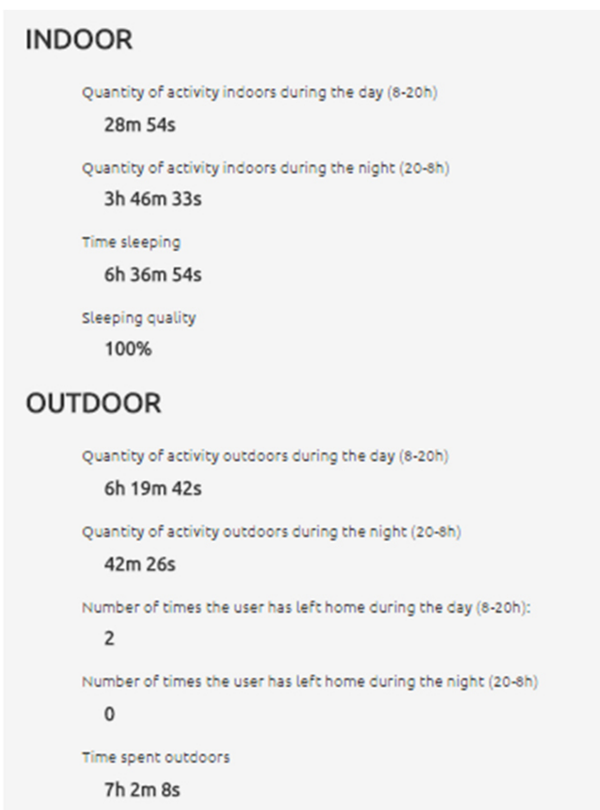

Figure 3: An example of summary of mobility activities

In order to cope with the data necessities of the actors of the system (*i.e.*, therapists, caregivers, relatives, and end-users themselves), an Intelligent Monitoring (IM) system has been designed. It aims to continuously mine the data through 5-dimensions: detection of emergencies, activity recognition, event notifications, summary extraction, and rule triggering. In order to meet these objectives, IM is composed of the following modules (see Figure 2): PP, the pre-processing module to encode the data for the analysis; ED, the emergency detection module to notify, for instance, in case of smoke or gas leakage; AR, the activity recognition module to identify location, position, activity- and sleeping-status of the user; EN, the event notification module to inform when a new event has been detected; SC, the summary computation module to perform summaries from the data; and RA, the risk advisement module to notify risks at run-time.

The healthcare center receives notifications, summaries, statistics, and general information belonging to the users through a web application. Figure 3 shows an example of a summary of mobility activities.

2.2 The quality of life assessment system

As stated above, IM is composed of six modules. Before going deeply in the QoL assessment system, which is the focus of this paper, let us summarize the role of each of these modules, the interested reader may refer to Ref.[9] for further details:

- PP. Its goal is to preprocess the data iteratively sending a chunk c to both ED and RA according to a sliding window approach. Starting from the overall data streaming, the system sequentially considers a range of time $|t_i - t_{i+1}|$ between a sensor measure s_i at time t_i and the subsequent measure s_{i+1} at time t_{i+1}. The output of PP is a window c from t_s to t_a, where t_s is the starting time of a given period and t_a is the actual time.
- ED. It aims to detect and inform about emergency situations for the end-users and about sensor-based system critical failures. Regarding the critical situations for the end-users, simple rules are defined and implemented to raise an emergency, when specific values appear on c. Regarding the system failures, ED is able to detect whenever user's home is disconnected from the middleware as well as when a malfunctioning of a sensor occurs. Each emergency is a pair $<s_i; l_{ei}>$ composed of the sensor measure s_i and the corresponding label l_{ei} that indicates the corresponding emergency. Once the ED finishes the analysis of c, the list of emergencies {e} is sent to the middleware, whereas c, filtered from the critical situations, is sent to AR.
- AR. Its goal is to recognize activities performed by the user. Currently, this module is able to recognize if the user is at home or away and if s/he is alone or not; the room in which the user is (no-room in case s/he is away, transition in case s/he moving from a

room to another); the activity status (*i.e.*, active or inactive); and the sleeping status (*i.e.*, awake or asleep). To recognize if the user is at home or away and if s/he is alone, we implemented a solution based on machine learning techniques.[10] The output is a triple $<t_s; t_e; l>$, where t_s and t_e are the time in which the activity has started and has finished, respectively, and l is a list of four labels that indicates: the localization (*i.e.*, home, away, or visits), the position ($i.e.$, the room, no-room, or transition), the activity status ($i.e.$, active or inactive), and the sleeping status (*i.e.*, awake or asleep).

- EN. It is able to detect events to be notified. Each event is defined by a pair $<t_i; l>$ corresponding to the time t_i in which the event happens together with a label l that indicates the kind of event. Currently, this module is able to detect the following events: leaving the home, going back to home, receiving a visit, remaining alone after a visit, going to the bathroom, going out of the bathroom, going to sleep, and awaking from sleep.
- SC. Once all the activities and events have been classified, measures aimed at representing the summary of the user's monitoring during a given period are performed. In particular, two kinds of summary are provided: historical and actual. The former gives a list of the activities performed during (i) the morning (*i.e.*, from 8 a.m. to 8 p.m.), (ii) the night (*i.e.*, from 8 p.m. to 8 a.m.), (iii) all the day, (iv) the week (from Monday morning to Sunday night), as well as (v) the month. The latter gives a report on: the room in which the user is; if the user is at home, or not; the number of times that s/he leaves the home; sleeping time; activity time; and number of visits per room.
- RA. It is aimed at advising therapist about one or more risky situations before they happen. The module executes the corresponding rules, defined by therapists through the healthcare center, at runtime according to the sequence of sensor measures coming from the PP as well the summary provided by the SC. A rule is a quadruple $<i; v; o; a_r>$, where i is the item that has to be verified (*e.g.*, a room, the number of slept hours) according to a given value v (*e.g.*, bedroom, 4 slept hours); o is the logic operator (*i.e.*, and, or, not) and a "null" operator in case there is only one term; and a_r is the action to be performed (*i.e.*, send a notification, an alarm, or an email).

The QoL assessment system is part of the SC module. It is composed of a set of sub-modules, each one devoted to assess a specific QoL item; namely: MOBILITY-assessment module; SLEEPING-assessment module; and MOOD-assessment module. Each sub-module is composed of two parts: Feature Extractor and Classifier. The Feature Extractor receives as input the list of notifications n coming from EN and the list of activities a from the AR and extracts the relevant features f to be given as input to the Classifier. The Classifier, then, uses those features to identify the right class Cl. This information will be then part of the overall summary $\sum$ provided as output by SC.

As stated above, three QoL items have been considered so far. Each Feature Extractor works with its proper list of features:

- MOBILITY: number of times the user left home, total time performing outdoor activities, total time performing activities (both indoors and outdoors), total time of inactivity, covered distance, number of performed steps, number of visited places, number of burned calories.
- SLEEPING: total sleeping time, hour the user went to sleep, hour the user woke up, number of times the user went to the toilet during the night, time spent at the toilet during the night, number of time the user went to the bedroom during the night, time spent at the bedroom during the night, number of sleeping hours the day before, number of sleeping hours in the five days before.
- MOOD: number of received visits, total time performing outdoor activities, total time performing activities (both indoors and outdoors), total time of inactivity, covered distance, number of performed steps, number of burned calories, hour the user went to sleep, hour the user woke up, number of times the user went to the toilet during the night, time spent at the toilet during the night, number of time the user went to the bedroom during the night, time spent at the bedroom during the night, number of sleeping hours the day before, number of sleeping hours in the five days before.

The Classifier is a supervised multi-class classifier built by using data previously labeled by the user and works on five classes, Very Bad, Bad, Normal, Good, and Very Good.

3 Results

To evaluate if the approach is effective in the task of automatically assessing QoL of people, we first installed the sensor-based system at 1 home in Barcelona. The selected user (SU) is an able-bodied 41-years-old woman who lives alone. The habits of SU have been monitored in the period from 01/11/2014 to 28/04/2015. A total of about 80 days have been considered to build the dataset that has been labeled by using the answers given by SU to the following questionnaire, each question in a scale from 1 to 5:

- How was your ability to move about?
- How did you sleep last night?
- How was your mood?

Let us note that not all the monitored days was usable due to several reasons, such as user's vacations, visits received during the day or because the user didn't answer the labelling questionnaire.

The dataset has been then divided in training-set and test-set and each classifier has been then evaluated through a k-fold validation approach. Performance of 7 different techniques has been compared in terms of F1 measure:[11] SVM, Logistic Regression, k-NN, Naïve Bayes, Decision Tree, Random Forest, and AdaBoost.

3.1 Mobility

A total of 82 labeled days have been used to assess MOBILITY. Since the user labeled them as Normal (44 times), Good (32 times) and Very Good (6 times), only those three classes have been considered to build the classifier.

Table 1 shows the results obtained during the testing phase; for each technique, the best configuration of parameters has been reported. In particular, we tried the approach considering only data (*i.e.*, features) from Moves (outdoor activities) and data from both Moves and the home-automation sensors (indoor and outdoor activities). As shown, in both configurations, SVM is the technique with best results. Moreover, the adoption of the home-automation sensors improves the performance.

The best classifiers have been then used with the test-set obtaining a F_1 of 0.569 considering only outdoor activities and a F_1 of 0.654 in case of considering both indoor and outdoor activities. Those results show that adopting indoor sensors improves the overall performance highlighting the usefulness of the adopted sensor-based system.

Table 1: Results obtained in assessing MOBILITY during the training phase

Classifier	Outdoor activities		Indoor and outdoor activities	
	Params	F_1	Params	F_1
SVM	C = 1000 γ = 0.008	0.699	C = 1 γ = 0.04	0.765
Logistics Regression	C = 1.693	0.662	C = 3.0	0.7645
kNN	k = 7	0.675	k = 3	0.684
Naïve Bayes	--	0.616	--	0.736
Decision tree	--	0.567	--	0.618
Random forest	estimators = 5	0.666	estimators = 100	0.700
AdaBoost	estimators = 50	0.620	estimators = 10	0.485

3.2 Sleeping

A total of 84 labeled days have been used to assess SLEEPING. The user labeled them as Bad (4 times), Normal (57 times), Good (23 times). Due to the small number of bad cases, we have built different kinds of classifiers: 3-classes (Bad, Normal, Good), 2-classes-vs1 (Normal, Good), and 2-classes-vs2 (Bad&Normal, Good). Table 2 shows the results during the training phase. In this case, best results have been obtained with a Random Forest approach in case of considering 3 classes and in case of considering only Normal and Good as classes. On the contrary, in case of considering together Bad and Normal, best results have been obtained by adopting an SVM, like in case of MOBILITY.

Table 2: Results obtained in assessing SLEEPING during the training phase

Classifier	3-classes		2-classes-vs1		2-classes-vs2	
	Params	F_1	Params	F_1	Params	F_1
SVM	C = 50 γ = 0.1	0.630	C = 200 γ = 0.005	0.711	C = 15 γ = 0.08	0.722
Logistics Regression	C = 0.01	0.597	C = 0.04	0.703	C = 1.69	0.716
kNN	k = 11	0.572	k = 9	0.634	k = 7	0.645
Naïve Bayes	--	0.563	--	0.598	--	0.560
Decision tree	--	0.607	--	0.653	--	0.616
Random forest	estimators = 5	0.656	estimators = 150	0.727	estimators = 100	0.704
AdaBoost	estimators = 50	0.648	estimators = 50	0.677	estimators = 10	0.692

The best classifiers have been then used with the test-set obtaining F1 of 0.654, 0.731, and 0.808, respectively. That means that the best solution consists of considering Bad and Normal together. Of course, in case we got samples covering all the given classes new solutions should be investigated.

3.3 Mood

A total of 80 labeled days have been used to assess MOOD. The user labeled them as Bad (1 time), Normal (44 times), Good (33 times), and Very Good (3 times). Due to answers given by the user, we decided to consider only 2 classes: Bad&Normal and Good&VeryGood. Moreover, we decided to perform experiments with all the features listed above as well as with a sub-set automatically selected (Figure 4 shows how features impact on the classification).

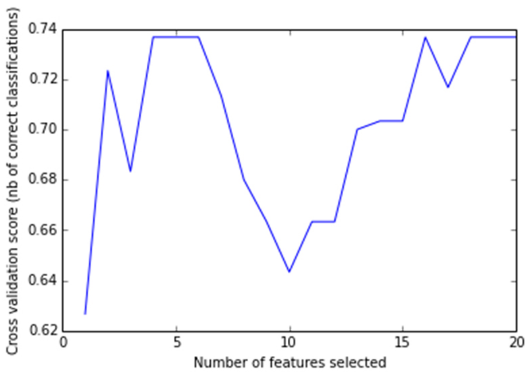

Figure 4: Impact of features in the classification task

Table 3 summarizes results obtained during the training phase. As shown, best results are obtained with a Random Forest considering a selected set of features. Nevertheless, during the test phase, best results have been given by using the Random forest with all the features, obtaining a F_1 = 0.739.

Table 3: Results obtained in assessing MOOD during the training phase

Classifier	All features		Selected features	
	Params	F_1	Params	F_1
SVM	C = 0.5 γ = 0.08	0.750	C = 100 γ = 0.002	0.776
Logistics Regression	C = 1.0	0.711	C = 9.0	0.776
kNN	k = 3	0.630	k = 3	0.759
Naïve Bayes	--	0.618	--	0.753
Decision tree	--	0.631	--	0.709
Random forest	estimators = 5	0.769	estimators = 100	0.814
AdaBoost	estimators = 50	0.711	estimators = 100	0.701

4 Related work

There is a large literature on recognition of activities at home.[12,13] A former study[14] already points out some of the difficulties in discriminating daily life activities based only on binary sensors data. The automatic recognition system was based on rules defined from the context and the duration of the activities to identify. The data of the study were obtained from 14 days of monitoring activities at home. A more exhaustive work regarding the use of switch and motion sensors for tracking people inside home is found in Ref.[15] Tests were done with up to three simultaneous users. High performances were reported by the trained tracking models. In Ref.[16] a more complex template learning model (SVM) was used to automatically recognize among 11 different home activities. The proposed technique was integrated in different window sliding strategies (*e.g.* weighting sensor events, dynamic window lengths, or two levels of window lengths). They used 6 months of data from 3 different homes in which activities such as “entering” or “leaving home” were monitored. In a more extensive work[17] they use Naïve Bayes, Hidden Markov Models (HMM) and Conditional Random Fields for the activity recognition problem. In that study, 7 smart environments were used and 11 different data sets were obtained and several activities were attempted to be recognized. In Ref.,[18] authors proposed a hybrid approach to recognize ADLs from home environments using a network of binary sensors. The hybrid system proposed was composed by using an SVM to estimate the emission probabilities of an HMM.

One upper level of complexity was added when researchers started investigating motor disorders and the possibility of utilizing wearable technology to assess the effect of clinical interventions on the quality of movement observed while patients performed functional tasks.[19] Solutions have been also proposed to monitor health and wellness through wearable and ambient sensors.[20,21] From the user perspective and with the goal of empower patients and, more generally, users, a lot of systems and mobile apps have been currently available to monitor mobility and/or sleep quality. The majority of them rely on wearable sensors, such as bracelets or smart-watches.

The study proposed in this paper differs from those cited above because it is not only aimed at recognizing activities but also at assessing QoL, in terms of MOBILITY, SLEEPING, and MOOD. For our best knowledge this is the first attempt to use a context-aware approach to automatically assess QoL items. Thus, no comparisons with other systems may be given. Let us also stress the fact that the sensor-based system, besides informing about the QoL of people, gives also general information to therapists and caregivers regarding user’s mobility ability, quality of sleep, and mood.

5 Discussion

Results presented in this paper show that 3 quality-of-life items (namely, MOBILITY, SLEEPING, and MOOD) can be inferred with a high accuracy (0.76, 0.72, and 0.81, respectively) by relying on an automatic QoL assessment system. Let us note that SLEEPING was the method with the lowest performance. This is due to the fact that, currently, the system uses only motion sensors. Higher performances could be expected when combining motion sensors with other ones, such as mat-pressure or light sensors. MOBILITY achieved higher performance results than SLEEPING especially when outdoor and indoor features are merged together. In fact, using only outdoor features was not as reliable as combining with indoor. This can be due to the reliability of the GPS system embedded in the smartphone that made some errors in identifying when the user was really away. Let us also note that this is an important result because disable people in general spend a lot of time at their home. Finally, MOOD reported the highest performances. Although at a first instance this could be surprising, this fact might be explained considering the intrinsic correlation between SLEEPING and MOBILITY, as highlighted by the questionnaire compiled daily by the users. It is worth noting that higher performances could be expected considering also social networking activities performed by the user.

Under the umbrella of the EU project BackHome, we tested our approach with three users with severe disabilities (both cognitive and motor) living at their own real homes. After only 3 weeks of testing, our approach seemed convincing also in the case of disabled people. It is worth noting that, as mentioned in the Introduction, answers to QoL questionnaires are completely subjective and depend on the particularity of each monitored user. In other words, the proposed solution has to be customized for each user. Hence, the classifier has to be trained by using data previously labeled by the specific user who must to answer the questionnaire. Nevertheless, we are currently studying if an online solution that starts from a given classifier and updates it accordingly to data from the real user, when available, may be adopted in order to reduce the cold-start problem implicit in the current solution.

As for the future work, we are considering ensemble of classifier to improve the overall performance of the QoL assessment system. Preliminary tests, in fact, show that merging together different classifier may improve the overall performance. Finally, to limit the intrinsic problem due to the labelling activities and, in particular, the fact that some classes may be no representative (as in our case for "Very Bad" and "Bad"), we are studying how to make a retraining activity once a good number of examples has been obtained.

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References

[1] Murphy B, Herrman H, Hawthorne G, *et al*. Australian WHOQoL instruments: User's manual and interpretation guide. Melbourne, Australia: Australian WHOQOL Field Study Centre; 2000.

[2] Group TE. EuroQol-a new facility for the measurement of health-related quality of life. Health policy. 1994; 16(3): 199-208.

[3] Hays RD, Morales LS. The RAND-36 measure of health-related quality of life. Annals of medicine. 2001; 33(5): 350-7. PMid:11491194. http://dx.doi.org/10.3109/07853890109002089

[4] Ware JE, Kosinski M, Dewey JE. How to score version 2 of the SF-36 health survey (standard & acute forms). QualityMetric Incorporated; 2000.

[5] O'Sullivan SB, Schmitz TJ, Fulk G. Physical rehabilitation. FA Davis; 2013.

[6] Vargiu E, Ceccaroni L, Subirats L, *et al*. User Profiling of People with Disabilities - A Proposal to Pervasively Assess Quality of Life. In: ICAART 2013 - Proceedings of the 5th International Conference on Agents and Artificial Intelligence, Volume 2, J. Filipe, A. L. N. Fred (Eds.); 2013.

[7] Vargiu E, Fernández JM, Miralles F. Context-aware based quality of life telemonitoring. Distributed Systems and Applications of Information Filtering and Retrieval. Springer Berlin Heidelberg; 2014. p. 1-23.

[8] Miralles F, Vargiu E, Dauwalder S, *et al*. Brain Computer Interface on Track to Home. The Scientific World Journal. 2015.

[9] Rafael-Palou X, Vargiu E, Dauwalder S, *et al*. Monitoring and Supporting People that Need Assistance: the BackHome Experience. DART 2014: Revised and Invited Papers. C. Lai, A. Giuliani and G. Semeraro (eds.), in press.

[10] Rafael-Palou X, Vargiu E, Serra G, *et al*. Improving Activity Monitoring through a Hierarchical Approach. ICT for Ageing Well. 2015.

[11] Van Rijsbergen CJ. Information Retrieval (2nd ed.). Butterworth; 1979.

[12] Van Kasteren T, Noulas A, Englebienne G, *et al*. Accurate activity recognition in a home setting. Proceedings of the 10th international conference on Ubiquitous computing. ACM; 2009. p. 1-9.

[13] Ye J, Dobson S, McKeever S. Situation identification techniques in pervasive computing: A review. Pervasive and mobile computing. 2012; 8(1): 36-66. http://dx.doi.org/10.1016/j.pmcj.2011.01.004

[14] Tapia EM, Intille SS, Larson K. Activity recognition in the home using simple and ubiquitous sensors. Springer Berlin Heidelberg; 2004.

[15] Wilson DH, Atkeson C. Simultaneous tracking and activity recognition (STAR) using many anonymous, binary sensors. Pervasive computing. 2005: 62-79. Springer Berlin Heidelberg.

[16] Krishnan NC, Cook DJ. Activity recognition on streaming sensor data. Pervasive and Mobile Computing. 2014; 10: 138-54. PMid:24729780. http://dx.doi.org/10.1016/j.pmcj.2012.07.003

[17] Cook DJ. Learning setting-generalized activity models for smart spaces. IEEE intelligent systems. 2010; 99: 1.

[18] Ordónez FJ, de Toledo P, Sanchis A. Activity recognition using hybrid generative/discriminative models on home environments using binary sensors. Sensors. 2013; 13(5): 5460-77. PMid:23615583. http://dx.doi.org/10.3390/s130505460

[19] Bonato P. Advances in wearable technology and applications in physical medicine and rehabilitation. Journal of Neuro Engineering and Rehabilitation. 2005; 2(1): 2. PMid:15733322. http://dx.doi.org/10.1186/1743-0003-2-2

[20] Biswas J, Tolstikov A, Jayachandran M, *et al*. Health and wellness monitoring through wearable and ambient sensors: exemplars from home-based care of elderly with mild dementia. Annals of telecommunications-annales des télécommunications. 2010; 65(9-10): 505-21.

[21] Miralles F, Vargiu E, Casals E, *et al*. Automatically Assessing Movement Capabilities through a Sensor-Based Telemonitoring System. International Journal of E-Health and Medical Communications. 2015 October-December; 6(4): 40-9.