A Method for Simplified HRQOL Measurement by Smart Devices

Chishu Amenomori, Teruhiro Mizumoto(✉), Hirohiko Suwa, Yutaka Arakawa, and Keiichi Yasumoto

Nara Institute of Science and Technology, Ikoma, Nara 630-0192, Japan
teruhiro.mizumoto@ieee.org
http://ubi-lab.naist.jp/

Abstract. Health-related quality of life (HRQOL) is a useful indicator that rates a person's activities in various physical, mental and social domains. Continuously measuring HRQOL can help detect the early signs of declines in these activities and lead to steps to prevent such declines. However, it is difficult to continuously measure HRQOL by conventional methods, since its measurement requires each user to answer burdensome questionnaires. In this paper, we propose a simplified HRQOL measurement method for a continuous HRQOL measurement which can reduce the burden of questionnaires. In our method, sensor data from smart devices and the questionnaire scores of HRQOL are collected and used to construct a machine-learning model that estimates the score for each HRQOL questionnaire item. Our experiment result showed our method's potential and found effective features for some questions.

Keywords: Health related quality of life (HRQOL) WHOQOL · Biological information · Location information

1 Introduction

Worldwide concern is growing over the issue that increases in hard work and stress are reducing people's abilities to perform various physical, mental, and social activities. People experience declines in their physical and mental functions when they continue to perform stressful activities for a long time, and they might even experience the following: melancholy [1], cognitive decline [2], and lifestyle-related diseases [3]. To prevent a performance decline in physical and mental activities, we must identify its early signs to prevent it. In particular, many Japanese people tend to rank their own personal satisfaction lower than other countries [4]. This attitude could cause a decline of activities.

Quality of Life (QOL) is an indicator that assesses the satisfaction and quality of our daily lives. Health-related quality of life (HRQOL), which is one element of QOL, is a useful indicator that evaluates the quality of life in such domains as physical and psychological health, social relationships, and economic and vocational status. We believe that HRQOL is an appropriate indicator to find the

© ICST Institute for Computer Sciences, Social Informatics and Telecommunications Engineering 2018
P. Perego et al. (Eds.): MobiHealth 2017, LNICST 247, pp. 91–98, 2018.
https://doi.org/10.1007/978-3-319-98551-0_11

signs of decline in physical, mental, and social activities. If we can automatically and continuously measure HRQOL, we may be able to detect the signs of its decline early and prevent that decline. However, since HRQOL measurements require users to answer many questions every day, its daily measurements impose a heavy burden. In existing research, even though many studies are estimating HRQOL using smart devices, they remain unimplemented [5,6].

In this paper, for the continuous measurement of HRQOL, we propose a simplified HRQOL measurement method which reduces the burden for answering a questionnaire and makes estimates from actually measured data. In our proposed method, we collect sensor data from a wrist-type sensor and a smartphone as well as the scores of the questionnaire items of WHOQOL-BREF, which is one HRQOL measurement method. We construct a machine-learning model from the collected data to estimate the score of each HRQOL questionnaire item with the Random Forest algorithm and use the collected sensor data and the questionnaire scores as features and correct answers, respectively.

To evaluate the accuracy of the models, we conducted a leave-one-out cross-validation and collected data from one participant for 15 weeks. In the evaluation, we also analyzed the effect of the features on each questionnaire item. We achieved an F-score of up to 87.9% and found that each questionnaire item has specific effective features. We also found that accuracy can be improved by feature selection. This paper makes two contributions. First, it proposes the first method that easily measures HRQOL by smart devices. Second, we analyzed the effects of the features extracted from the data measured by smart devices for each questionnaire item.

2 HRQOL Overview

2.1 Definition

The World Health Organization (WHO) defines QOL as "an individual's perception of their position in life in the context of the culture and value systems in which they live, and in relation to their goals, expectations, standards and concerns" [7]. Spilker classified QOL under five domains: (1) physical status and functional abilities; (2) psychological status and well-being; (3) social interactions; (4) economic and/or vocational status; and (5) religious and/or spiritual status [8]. Each domain contains associated components: daily behavior and medical institutions for (1), body appearance and self-evaluation for (2), human relationships and social supports for (3), economic resources and transportation for (4), and such activities as faith, worship, and memberships in organizations for (5). QOL can be classified into health-related quality of life (HRQOL) and non-health related quality of life (NHRQOL).

HRQOL represents a QOL that is directly influenced by health, disease, and medical intervention. Existing methods ask questions that correspond to each domain of QOL to measure HRQOL. NHRQOL represents a QOL that is not directly influenced by medical intervention, such as the environment, the economy, and politics [9].

Since our final goal in this study is the early detection of the signs of stress and its prevention, we focus on measuring HRQOL, which is strongly related to physical and mental health states.

2.2 HRQOL Evaluation Method

The answering scale differs depending on the individual, because HRQOL is an indicator of the personal satisfaction felt by individuals. Even for the same person, the scale changes depending on her context, such as her mental state. Various methods for quantitatively evaluating HRQOL have been proposed, including the Sickness Impact Profile (SIP), Short Form-36 (SF-36), WHOQOL [10], WHOQOL-BREF [11], etc. Even though WHOQOL is recognized worldwide, its questionnaires have too many items. So WHOQOL-BREF was developed by a simplified WHOQOL. Since WHOQOL-BREF's policy resembles our method that aims to continuously and simply measure HRQOL, we propose a simpler measurement method based on WHOQOL-BREF.

3 Related Work

Many surveys have addressed the relationship between HRQOL and such individual attributes as activity and ability. Brown et al. [12] revealed the relationship between HRQOL and physical activity and collected physical activity data and answers to four questions related to HRQOL developed by the U.S. Centers for Disease Control and Prevention from 175,850 adults. However, the questionnaire survey was only given once to the participants, unlike our method that measured for long time. Sörensen et al. [13] identified the relationship between HRQOL and the working capacity of middle-aged men in blue-collar occupations. They measured the working capacity index (WAI) and HRQOL scores by Rand-36 from 196, 40–60 year old men. They found a relationship between HRQOL and working capacity and suggested that improving the latter might benefit QOL. However, this study just focused on physical health.

Some studies have used smart devices to measure stress levels. Garcia-Ceja et al. [14] used the accelerometer data of smartphones to detect stress in a working environment and achieved a maximum overall accuracy of 71% for user-specific models. Sano et al. [15] used wrist sensors and smartphones to recognize stress. They collected Three-axis accelerometer data and skin temperatures and conductance from wrist sensors and the usage of smartphones of 18 subjects over five days. They achieved over 75% accuracy of low and high perceived stress recognition using a combination of mobile phone usage and sensor data. However, these indicators for evaluating stress were not constructed based on any standard method for stress measurement.

As shown above, since almost all HRQOL surveys have been carried out using questionnaires, they have not done to continuously conduct long-term QOL measurements. Some studies used smart devices to make their own evaluation standards and focused on a specific activity or mental state. In this study, we achieved a simple and continuous method for HRQOL estimation with high accuracy under globally established evaluation standards.

4 Simplified HRQOL Measurement Method

4.1 Overview

We propose a simplified HRQOL measurement method to estimate HRQOL scores from life log data that are measured and collected by a wristband and a smartphone (Fig. 1). The HRQOL estimation model is constructed by the Random Forest algorithm, which is one machine-learning algorithm. This method reduces the burden of questionnaire responses and enables real-time measurements.

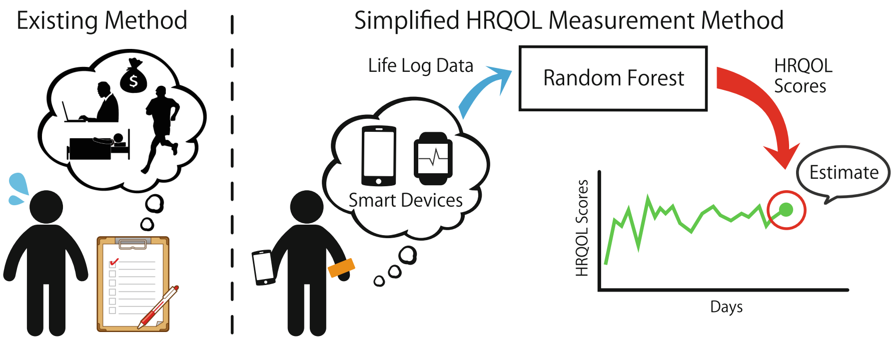

Fig. 1. Method's overview

4.2 Devices and Features

We used an E4 wristband [16] and a smartphone to measure the life log data. An E4 wristband is a smart device that can measure acceleration (ACC), electrodermal activity (EDA), blood volume pulse (BVP), heart rate (HR), inter-beat interval (IBI), and skin temperature (TEMP). The following are the sampling frequencies of each sensor: BVP, 64 Hz; ACC, 32 Hz; EDA, 4 Hz; HR and TEMP, 1 Hz. IBI irregularly gets data.

First, we identified the sleeping time and the activity (rising) time as status. Next we calculated the following seven features for each of six kinds of sensor data measured by the E4 wristbands: total, average, median, standard deviation, variance, maximum, and minimum. Moreover, we calculated the BVP-LF/HF ratio [17] and the HR-LF/HF ratio every five minutes and used four features: total, maximum, minimum, and the number of times the average was exceeded.

The smartphone collects location data at ten minute intervals and generates six features: total moving distance, moving distance around the home, time staying at home/workplace, sleeping place, and farthest distance from the wake-up position based on location data.

4.3 HRQOL Estimation Model

We constructed an HRQOL estimation model using machine learning with the Random Forest algorithm. The model was implemented using scikit-learn, which is one type of Python library.

In the basic model, the 109 input features are explained in Sect. 4.2. As the training data, we used the WHOQOL-BREF questionnaire results answered by the participant. We applied the leave-one-out cross-validation method and evaluated the estimation accuracy.

5 Preliminary Results

In this section, we evaluate the accuracy of our proposed estimation model through preliminary experiments.

5.1 Purpose

The purpose of our experiment is to evaluate the accuracy of the proposed model and show the feasibility of the simplified measurement method that reduces the burden of questionnaire responses. We investigated the accuracy of HRQOL estimation based on the log data obtained from the smart devices as well as important features that affect the estimation accuracy.

5.2 Overview

Life log data were collected for 15 weeks from a 23-year-old male participant with a wearable device and a smartphone. He answered a WHOQOL-BREF questionnaire every day based on the actual activities of his day. The WHOQOL-BREF question items are shown in Table 1. WHOQOL-BREF has four domains: physical health (PHY), psychological (PSY), social relationships (SOC), and environment (ENV).

During the experiments, we placed no limitations on any aspect of his behavior; just instructed him to answer the questions every day. The dataset was created by removing the daily data if participant forgot to answer the questions or there was data lost from the smart devices. As a result, the dataset contains 100 days of data.

The HRQOL estimation model, which was constructed by Random Forest based on the dataset, was validated by the leave-one-out cross-validation method.

5.3 Results

The 3rd to 5th columns of Table 1 respectively show the Precision, Recall, and F-scores when estimating the scores of each questionnaire item. The 6th column shows the variance of the scores for each item. Each item was answered from among five values: 1: not at all, 2: slightly, 3: moderately, 4: very, 5: extremely.

Table 1. WHOQOL-BREF

Item	Domain	Precision	Recall	F score	Variance	Question item [11]
Q1	-	0.423	0.490	0.440	0.927	How would you rate your quality of life?
Q2	-	0.552	0.571	0.550	0.797	How satisfied are you with your health?
Q3	PHY	0.348	0.357	0.351	0.783	To what extent do you feel that physical pain prevents you from doing what you need to do?
Q4	PHY	0.417	0.520	0.425	0.742	How much do you need any medical treatment to function in your daily life?
Q5	PSY	0.401	0.429	0.412	0.780	How much do you need any medical treatment to function in your daily life?
Q6	PSY	0.419	0.429	0.423	0.750	To what extent do you feel your life to be meaningful?
Q7	PSY	0.290	0.327	0.299	0.671	How well are you able to concentrate?
Q8	ENV	0.437	0.541	0.470	0.603	How safe do you feel in your daily life?
Q9	ENV	0.413	0.480	0.409	0.753	How healthy is your physical environment?
Q10	PHY	0.451	0.480	0.457	0.810	Do you have enough energy for everyday life?
Q11	PSY	0.519	0.602	0.522	0.475	Are you able to accept your bodily appearance?
Q12	ENV	0.787	0.878	0.830	0.129	Have you enough money to meet your needs?
Q13	ENV	0.735	0.857	0.791	0.241	How available to you is the information that you need in your day-to-day life?
Q14	ENV	0.364	0.367	0.363	0.969	To what extent do you have the opportunity for leisure activities?
Q15	PHY	0.417	0.469	0.436	1.070	How well are you able to get around?
Q16	PHY	0.270	0.327	0.283	0.851	How satisfied are you with your sleep?
Q17	PHY	0.450	0.520	0.479	0.632	How satisfied are you with your ability to perform your daily living activities?
Q18	PHY	0.331	0.449	0.315	0.789	How satisfied are you with your capacity for work?
Q19	PSY	0.417	0.510	0.412	0.644	How satisfied are you with yourself?
Q20	SOC	0.464	0.469	0.419	0.606	How satisfied are you with your personal relationships?
Q21	SOC	0.843	0.918	0.879	0.081	How satisfied are you with your sex life?
Q22	SOC	0.609	0.724	0.629	0.267	How satisfied are you with the support you get from your friends?
Q23	ENV	0.735	0.857	0.791	0.173	How satisfied are you with the conditions of your living place?
Q24	ENV	0.806	0.898	0.850	0.093	How satisfied are you with your access to health services?
Q25	ENV	0.752	0.867	0.806	0.131	How satisfied are you with your transport?
Q26	PSY	0.560	0.561	0.487	0.844	How often do you have negative feelings such as blue mood, despair, anxiety, depression?

The estimation accuracy of such question items in the SOC and ENV domains as Q12, Q13, Q21, Q22, Q23, Q24, and Q25 exceeds the question items of the PHY and PSY domains. One possible reason is that the answers for the SOC and ENV items do not change very frequently. In fact, their variance is smaller than the other items. In our data, changes in those items appeared when the participant went on a business trip. Therefore, for SOC/ENV, it will be effective to sent questionnaire prompts only when triggers for the changes appeared, e.g., business trips.

On the other hand, since the estimation accuracy is low in the PHY and PSY domains, perhaps some unrelated features should have been used to train the model. So we focused on two items (Q3 and Q5) and re-estimated them using some selected features. For feature selection, we added features one by one in the order of their importance with the Gini coefficient method and repeated it until the estimation accuracy became maximum.

Q3 is in the PHY domain. Q3's accuracy improved from 0.351 to 0.502 as a result of selecting seven features. We selected these five features in the activity time: EDA and HR medians, EDA and HR averages, HR minimum, and two sleep time features: average and maximum TEMP.

Q5 is in the PSY domain. Q5's accuracy improved from 0.412 to 0.547 as a result of selecting ten features. Four of the selected features were based on location data: farthest distance from his wake-up position, total moving distance and staying time at home/workplace; three activity time features: total of composite acceleration, HR median, and BVP variance; three features in the sleep time: maximum of BVP-LF/HF ratio, standard deviation of TEMP, and BVP total.

We found that the features that improved the estimation accuracy were different among the question items. Thus, we must select suitable features for each question item. Extracting suitable features for all 26 items and estimating their accuracy is future work.

6 Conclusion

In this paper, we proposed a simplified HRQOL measurement method that reduces the burden of answering questionnaires to achieve continuous HRQOL measurements. The proposed method utilizes sensor data from smart devices and the questionnaire scores of HRQOL and constructs a machine-learning model to estimate the score for each questionnaire item by the Random Forest algorithm.

In the experiment, we estimated the questionnaire response values from life log data, obtained estimation accuracy that was higher in the social relations and the environmental domain, and achieved an F-score of up to 87.9%. We also improved the estimation accuracy by feature selection for each question item.

Future work will improve the accuracy by feature selection for each questionnaire item. Moreover, based on the user's situation, we will investigate how much the user burden can be reduced by changing the frequency of the questionnaires. We will also apply the proposed method to larger datasets obtained from many diverse participants.

Acknowledgment. This work is partly supported by JSPS KAKENHI Grant Number 16H06980, Grants-in-Aid for Humanophilic Innovation Project, and Health and Labor Sciences Research Grants (201621010A).

References

1. Larun, L., Nordheim, L.V., Ekeland, E., Hagen, K.B., Heian, F.: Exercise in prevention and treatment of anxiety and depression among children and young people. The Cochrane Library (2006)
2. Biddle, S.: Physical activity and mental health: evidence is growing. World Psychiatry **15**(2), 176–177 (2016)

3. Babazono, A., Kame, C., Ishihara, R., Yamamoto, E., Hillman, A.L.: Patient-motivated prevention of lifestyle-related disease in Japan: a randomized, controlled clinical trial. Dis. Manage. Health Outcomes **15**(2), 119–126 (2007)
4. Cabinet Office, Government of Japan: International Survey of Youth Attitude (2013). http://www8.cao.go.jp/youth/english/survey/2013/pdf_index.html
5. van Uem, J.M.T.: A viewpoint on wearable technology-enabled measurement of wellbeing and health-related quality of life in parkinson's disease. J. Parkinson's Dis. **6**(2), 279–287 (2016)
6. Gonçalves, J., Faria, B.M., Reis, L.P., Carvalho, V., Rocha, Á.: Data mining and electronic devices applied to quality of life related to health data. In: 10th Iberian Conference on Information Systems and Technologies (CISTI) 2015, pp. 1–4. IEEE (2015)
7. The WHOQOL Group. The development of the world health organization quality of life assessment instrument (the WHOQOL). In: Orley, J., Kuyken, W. (eds.) Quality of Life Assessment: International Perspectives. Springer, Heidelberg (1994). https://doi.org/10.1007/978-3-642-79123-9_4
8. Spilker, B.: Quality of Life and Pharmacoeconomics in Clinical Trials, pp. 1–10. Lippincott Williams & Wilkins, New York (1996). Chapter Introduction
9. Kirita, T., Omura, K. (eds.): Oral Cancer. Diagnosis and Therapy, vol. 3. Springer, Tokyo (2015). https://doi.org/10.1007/978-4-431-54938-3
10. THE Whoqol GROUP: The world health organization quality of life assessment (WHOQOL): development and general psychometric properties. Soc. Sci. Med. **46**(12), 1569–1585 (1998)
11. World Health Organization et al. WHOQOL-BREF: Introduction, Administration, Scoring and Generic Version of the Assessment: Field Trial Version, December 1996 (1996)
12. Brown, D.W., et al.: Associations between recommended levels of physical activity and health-related quality of life findings from the 2001 behavioral risk factor surveillance system (BRFSS) survey. Prev. Med. **37**(5), 520–528 (2003)
13. Sörensen, L.E., Pekkonen, M.M., Männikkö, K.H., Louhevaara, V.A., Smolander, J., Alén, M.J.: Associations between work ability, health-related quality of life, physical activity and fitness among middle-aged men. Appl. Ergon. **39**(6), 786–791 (2008)
14. Garcia-Ceja, E., Osmani, V., Mayora, O.: Automatic stress detection in working environments from smartphones' accelerometer data: a first step. IEEE J. Biomed. Health Inf. **20**(4), 1053–1060 (2016)
15. Sano, A., Picard, R.W.: Stress recognition using wearable sensors and mobile phones. In: 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction (ACII), pp. 671–676. IEEE (2013)
16. Real-time physiological signals - e4 eda/gsr sensor. https://www.empatica.com/e4-wristband
17. Malik, M.: Heart rate variability. Ann. Noninvasive Electrocardiol. **1**(2), 151–181 (1996)