Detecting impending malnutrition of elderly people in domestic smart home

Authors:
Friedrich, Björn, Carl von Ossietzky University Oldenburg, Assistance Systems and Medical Device Technology, bjoern.friedrich@uni-oldenburg.de
Bauer, Jürgen, University of Heidelberg, Geriatric Centre, juergen.bauer@bethanien-heidelberg.de
Hein, Andreas, Carl von Ossietzky University Oldenburg, Assistance Systems and Medical Device Technology, andreas.hein@uni-oldenburg.de

Abstract
Proper nutrition is very important for the well-being and independence of elderly people. A significant loss of body weight or a decrease of the Body Mass Index respectively is an indicator for malnutrition. A continuous monitoring of the BMI enables doctors and nutritionists to intervene on impending malnutrition. However, continuous monitoring of the BMI by professionals is not applicable and self-monitoring not reliable. In this article a method for monitoring the trend of the BMI based on ambient sensors is introduced. The ambient sensors are used to measure the time a person spends for preparing meals at home. When the trend of the average time for 4 weeks changes, so does the trend of the BMI for those 4 weeks. Both values show a very strong correlation. Thus, the average time for preparing a meal is a suitable indicator for doctors and nutritionists to examine the patient further, become aware of an impending malnutrition, and intervene at an early stage of malnutrition. The method has been tested on a real-world dataset collected during a 10-month field study with 20 participants of an age of about 85 years.

1 Introduction
People in general need nutritional balance and especially elderly do. As older people grow as more they are losing function and performance. Malnutrition accelerates this process especially for elderly people. The loss of function and performance leads to a decrease in independence and well-being. Studies show that malnutrition of the elderly is a problem of international interest [9] [2]. Malnutrition has several effects, among others a loss in recovering abilities, psychological condition and a loss in strength [16] [17]. Enhancing the nutrition with proteins has been proven useful to treat the symptoms of malnutrition [13]. One indicator for malnutrition is the significant loss of body weight and hence a significant decrease of the BMI. Guidelines on enteral nutrition consider a loss of more than 5 % in 3 months or more than 10 % in 6 months of the body weight and a BMI smaller than 20 \( \frac{kg}{m^2} \) as an indicator for malnutrition [9] [2]. A continuous monitoring of the BMI enables doctors to investigate the cause of major fluctuations of the body weight and choose a proper treatment at an early stage of an impending malnutrition. However, a continuous monitoring of the BMI by professionals is not applicable and self-monitoring tends to be unreliable. Low-cost, unobtrusive ambient sensor systems are well-accepted among the group of elderly people and installed in a flat a way for continuous monitoring [12]. In this article a method for monitoring the BMI using data of motion and door contact sensors, and power consumption sensors is introduced. The basic idea is to compute the time spent preparing for meals per week and the trend. The Spearman correlation coefficient is computed for the trends. Both trends show a very strong correlation according to [7]. This method is validated on a real-world dataset with 20 elderly participants. This article is structured as follows. The Section State of the Art is a short survey of existing approaches to measure the BMI automatically, and to monitor nutritional intake using information technology. In Materials and Methods the OTAGO study for collecting the data, the preprocessing of the dataset, and the used
algorithms are explained. In Section 4 the results are shown. The discussion of the results can be found in Section 5. In the last section conclusions are drawn from results and discussion.

2 State of the Art

There are only a few approaches to measure the BMI using a sensor system designed for that specific purpose. The sensor systems are automatically measuring the height and the body weight of a person and calculate the BMI. The systems are basically comprised of an ultrasonic proximity sensor for measuring the height, a weight sensor for measuring the weight and a microcontroller as computing and data processing unit [1] [3] [5]. The low-cost sensor systems are explicitly designed for one purpose and cannot be used for other applications. The systems were designed for use in a private home by the inhabitant without supervision of a professional. So, the results are prone to errors. The person might step on the sensor wearing clothes or while carrying things. Especially, if the sensors are installed in a frequently used space. In [6] an approach for using a medical air-displacement plethysmography device, for measuring the body fat and BMI is introduced. This device can be used by people at home. Since this special equipment is very expensive and invasive it is not applicable for most people and especially not for the elderly. Moreover, the patient might forget to use it or uses it in a wrong way and hence the results are not reliable. Instead of drawing inferences from the BMI about the nutrition many approaches for measuring the nutrition directly exists.

Since smartphones became broadly available many approaches are utilising smartphones and the built-in cameras for monitoring the nutritional intake. Common approaches are questionnaires as an application on the phone, nutrition dairies and classification of the food or ingredients based on camera data [12] [8] [15]. All those approaches are relying on a food database and if the food at hand is not in the database the person must update the database manually. This procedure is complicated and not applicable for elderly people. Most applications are not designed for elderly people and makes it hard or impossible to use. Another approach is based on smart fridges. The fridge can detect which food or ingredients is removed and compute the nutritional intake on that data. Since the fridge is not able to measure the amount the results are an estimation [11]. The potential of ambient sensors in smart homes have been explored recently as well. In [10] a system in a smart home in combination with a questionnaire on a smartphone is described. The questionnaire was validated and a usability test with elderly people was made. However, the sensor system has not been evaluated with real world data of elderly people. A comprehensive survey of nutrition monitoring using information technology and the difficulties for the elderly using them can be found in [14].

The sensor systems designed for measuring the BMI are likely to be used in a wrong manner and cause false values. The approaches using smartphones are not feasible for elderly people, because interaction is needed, and the applications are not optimised for elderly people. The most promising approach is the smart home sensor system. However, there was no evaluation with target group.

3 Materials and Methods

3.1 Data Acquisition

The dataset has been collected during the OTAGO study conducted from July 2014 to December 2015 by the Carl von Ossietzky University of Oldenburg. The participants in the study were 84.74 years old and 17 of the 20 participants were female and 3 were male. The planned participation time was 40 weeks for each participant. Due medical condition, moving and death some participants dropped out of the study and the average participation time became 36.5 weeks. During the study several standardised geriatric assessments under the supervision of a professional physicist have been performed and physical parameters like BMI have been recorded. Additionally, standardised questionnaires have been used to evaluate the independence and mental condition among others. The assessments have been performed on the first day of the study and then every 4 weeks. Due to public holidays, visitors and time conflicts the average time between two assessment and data collection days were 31.3 days (±5.3 days).

During the study a multi-component sensor system were installed in the flats of the participants. Basically, two types of sensors were used. The first type were power consumption sensors and the second type home automation sensors. The home automation sensors were motion sensors installed in the rooms and door sensors installed at the main doors and the fridge of the flats. The sensors were connected wirelessly to the base station. The flats of the participants have different layouts and a different set of installed sensors, because the participants were free to choose the sensors installed in their flats.

![Sensor Diagram](image)

*Figure 1 The flats of two participants of the OTAGO study. The layout and size of the flats are different and so the installed sensors are. In the right flat plenty of sensors are installed, especially in the kitchen and the hallway.*

The study has been conducted under the ethic vote No. Drs27/2014 and in accordance with the Declaration of Helsinki.

### 3.2 Data Preprocessing

During the study the BMI of the participants has been measured around about every four weeks. Dates with missing values have been removed and the corresponding weeks were not considered. Besides missing BMI values there were missing sensor data as well. This was related to sensor failure and two participants moved to short-term care and their sensor system was shut down for that time. Those times are not considered either. For each two of the BMI values the recorded sensor data between those two dates has been processed. At first all data from sensors not of interest were discarded. Sensors of interest are power consumption sensors attached to appliances in the kitchen, motion sensors in the kitchen, and the door contact sensor in the fridge. The data of all available sensors in the kitchen was considered. Since the sensor setup is heterogenous, the considered sensors may vary from participant to participant. After selecting the sensors of interest, a filter was applied to the power consumption values. The power consumption sensors are measuring standby state of appliances as well and hence must be filtered to get the data of usage. The cleaned data were separated by week. Analysing the diaries of the participant revealed, that the schedule and activities are not varying much on a weekly scale. On a daily scale the variation is very high and would cause a high fluctuation in the computed values. So, the use of a weekly scale is feasible. For computing the duration of preparing a meal the home automation and power sensors were fused. The beginning of preparing a meal has been defined by the number of used appliances and activity in the kitchen. When an event from a motion or door contact sensor in the kitchen was present the following events are checked and if the following...
events are at least from the half of the sensors of the appliances, this moment is defined as the beginning of a meal preparation. The preparation is defined as finished, when the time between two events exceeds 60 minutes. The difference of the timestamp of the first event and the last event is the time spent for preparing the meal. This is done for every day of the week. Finally, the values are added up and divided by the number of days to get the average time spent for preparing a meal per day for the week at hand. This has been done for all participants for the whole duration of the study. Due to absence and non-uniform measurements of the BMI the number of values between two BMI measurements is non-uniform. Table 1 shows an example of the processed dataset.

Table 1 The samples of the processed dataset for two participants for the first nine weeks. Due to absence and the time between two BMI measurements the number of computed values between two BMI measurements are not uniform.

| Week | Time ID 1 | BMI ID 1 | Time ID 2 | BMI ID 2 |
|------|-----------|----------|-----------|----------|
| 1    | 115.1     | 23.01    | 50.1      | 27.77    |
| 2    | 104.6     |          | 179.1     |          |
| 3    | 103.2     |          | 122.6     |          |
| 4    | 127.4     | 25.65    | 351.9     | 25.38    |
| 5    | 111.8     |          | 215.8     |          |
| 6    | 108.6     |          | 426.1     |          |
| 7    | 121.0     |          | 200.2     | 22.89    |
| 8    | 118.9     |          | 341.3     |          |
| 9    | 132.6     | 26.14    | 664.6     |          |

3.3 Regression

A linear approach is used for modelling the trend of the BMI and the time for preparing meals. For modelling the relation of two variables a simple linear regression is a commonly used approach. In this case the scalar variable is the time and the dependent variable the BMI or the time for preparing meals respectively. A simple linear regression is defined as follows

\[ y_i = a \times x_i + b, i \in \{1, \ldots, n\} \]

where \( y_i \) is the dependant variable and \( x_i \) the scalar variable, \( i \) the index of the current samples and \( n \) the total number of samples. As objective function the least-squared function is used. Since the trend of the BMI for two consecutive values is considered the simple linear regression for those two values is an ordinary line crossing these two points. For two consecutive BMI values several values for preparing meals exist. Therefore, the simple linear regression satisfies the common optimisation approach.

4 Results

Overall, there is a high correlation between the change of the time spent for preparing meals and the change of the BMI. The Spearman correlation coefficient is at least greater than 0.9 or smaller than -0.9 with a p-value smaller than 0.001. The average of the absolute correlation coefficients for all months for each participant is shown in Table 2. Depending on the sensor combination the computed time for preparing meals strongly varies. The smallest time value is 6.3 minutes for preparing meals per day. The largest time value is 635.4 minutes for preparing meals per day. The algorithm did not detect any meal preparation for four participants. Two of the four participants have motion sensors in the kitchen and power consumption sensors attached to the kettle and the coffeemaker in the kitchen. The third had a door contact sensor in the fridge in addition, but there were no detections either. The fourth participant had to be admitted to a hospital and deceased. So, the data is insufficient for the algorithm. Even though the time for preparing meals is not feasible, the method still captures the trend. The trend of the time and the BMI are not always the same. Several times the time for preparing meals is decreasing, but the BMI is increasing and leading to a negative, but still significant, correlation. Figure 1 shows the result of the first month of participant 1. Participant 1’s flat was well equipped with sensors. Figure 2 shows the result of participant 14. Participant 14’s flat had only one motion
sensor and two power consumption sensors in the kitchen. Nevertheless, the trend of the computed time and the BMI shows a strong correlation.

Figure 2 Shows the trend and the values of the BMI and time of ID 1 of the first month. The correlation coefficient is greater than 0.9 and the p-value smaller than 0.001.

Figure 3 Shows the trend and the values of the BMI and time of ID 14 of the fourth month. The correlation coefficient is greater than 0.9 and the p-value smaller than 0.001.
Table 2 The average correlation coefficients for each participant. The absolute value of the correlation coefficient were added up and divide by their count.

| ID | Avg. correlation coefficient | BMI count | Time count | p-value |
|----|-------------------------------|-----------|------------|---------|
| 1  | 0.91                          | 10        | 28         | <0.001  |
| 2  | 0.95                          | 11        | 32         | <0.001  |
| 3  | 0.93                          | 11        | 35         | <0.001  |
| 4  | 0.94                          | 11        | 30         | <0.001  |
| 5  | 0.92                          | 11        | 37         | <0.001  |
| 6  | 0.94                          | 11        | 36         | <0.001  |
| 7  | 0.94                          | 11        | 32         | <0.001  |
| 8  | 0.97                          | 6         | 18         | <0.001  |
| 9  | 0.96                          | 9         | 9          | <0.001  |
| 10 | 0.92                          | 11        | 39         | <0.001  |
| 11 | N.A.                          | 8         | 2          | N.A.    |
| 12 | N.A.                          | 1         | 0          | N.A.    |
| 13 | 0.93                          | 8         | 10         | <0.001  |
| 14 | 0.94                          | 8         | 18         | <0.001  |
| 15 | 0.94                          | 11        | 26         | <0.001  |
| 16 | 1.0                           | 5         | 15         | <0.001  |
| 17 | N.A.                          | 1         | 0          | N.A.    |
| 18 | N.A.                          | 0         | 0          | N.A.    |
| 19 | 1.0                           | 5         | 6          | <0.001  |
| 20 | 0.95                          | 7         | 18         | <0.001  |

5 Discussion

The results show a very strong correlation between the change of the BMI and the change in time spent for preparing meals. Participants 16 and 19 have the largest correlation coefficient of all participants. Participant 16 has a fast decreasing BMI, and a fast decreasing time for meals. The explanation is that the participant had to undergo chemotherapy during the study. Chemotherapy has a lot of side effects. One is the massive loss of body weight and hence a decreasing BMI. During the therapy and the recovery phase after, the participant has been assisted by nurses and family members. They took responsibility for preparing meals among other things. This person was likely faster at preparing meals than the participant, that leads shorter time for preparation and so to a very strong correlation, but there is no coherence between the two values.

Participant 19 has a steadily increasing BMI and the time has a strong variation. Participant 19 has been admitted to the hospital for several treatments and one hip operation. Especially, the operation had a strong influence on the mobility and independence. During the recovery phase the participant did not prepare meals himself but got home-delivered meals. Those meals are already prepared and need to be reheated only. Reheating a meal leads to shorter time for meal preparation. The BMI was probably increasing, due to the reduction of mobility after the hip operation and the normal food intake. Like for participant 16 there is a very strong correlation, but no coherence. For four participants the algorithm did not detect any meal preparations. Excluding the deceased participant, a set of insufficient sensors can be identified. Considering the three participants the presence of a motion sensor, door contact sensor in the fridge and power consumption sensors attached to the coffeemaker and the kettle are insufficient to capture meal preparations. Adding an additional sensor to the microwave enables the algorithm to detect meal preparation. The power consumption sensor of the coffeemaker or the kettle can be removed without lowering the accuracy of the results. The participant with the smallest subset of sensors compared to the three mentioned before has a power consumption sensor for the microwave. However, the minimal subset of sensors is enough to measure the trend of the time, but not for computing feasible meal preparation times. The maximum
and minimum times are computed on data from a minimal set of sensors. The optimal sensor combination is one motion sensor in the kitchen, one door contact sensor in the fridge, one power consumption sensor for the microwave and at least one more power consumption sensors for one more appliances in the kitchen.

The algebraic sign of the correlation coefficient and information whether the trend of the time is increasing or decreasing, gives information about the direction of the trend of the BMI. Is the correlation coefficient positive and the trend positive as well, the BMI is increasing. Is the trend decreasing the BMI is decreasing as well. Is the algebraic sign negative and the trend decreasing, the trend of the BMI is increasing. Is the trend increasing, the BMI is decreasing.

6 Conclusion

In this article an approach for continuously measuring the trend of the BMI using home automation and power consumptions sensors has been introduced. Even though the situation and circumstances in private homes are varying a lot this approach has been successfully validated on a real-world dataset. The trend of the time spent for preparing meals can be used as an indicator for impending malnutrition. Based on this indicator doctors and nutritionists can do further examinations of the patient and take appropriate measures at an early stage of malnutrition or impede malnutrition at all. So, this approach contributes to support of the elderly to keep their independence and improve their well-being.

Acknowledgements

We acknowledge Bianca Sahlmann (University of Oldenburg) and Lena Elgert (Peter L. Reichertz Institute, Hannover) for performing the assessments. We acknowledge Enno-Edzard Steen (University of Oldenburg) for installing and setting up the sensors. The OTAGO study has been funded by an internal funding of the Carl von Ossietzky University of Oldenburg.

7 References

[1] Baladad, BM, JV Magsombol, JNB Roxas, JA Dolot, and E De Castro. “Development of Automated Body Mass Index Calculation Device.” May 2016, 11 ed.: 5192 - 5201.

[2] Berry, E, et al. “ESPEN Guidelines on Enteral Nutrition: Geriatrics.” Clinical Nutrition, April 2006: 330 - 360.

[3] Burhan, IU, FA Syed, and AA Ali. “Microcontroller Based Automated Body Mass Index (BMI) Calculator with LCD Display.” 2nd International Conference on Electrical, Electronics and Civil Engineering, Singapore, 2012. 162 - 164.

[4] Chen, J, L Gemming, R Hanning, and M Allman-Farinelli. “Smartphone apps and the nutrition care process: Current perspectives and future considerations.” Patient Education and Counseling, April 2018: 750 - 757.

[5] Dipika, M. “Measurement of Body Mass Index BMI using PIC 18F452 Microcontroller.” International Journal on Recent and Innovation Trends in Computing and Communication, January 2015, 2 ed.: 2213 - 2216.

[6] Fields, DA, and GR Hunter. “Monitoring body fat in the elderly: application of air-displacement plethysmography.” Current Opinion in Clinical Nutrition and Metabolic Care, January 2004, 7 ed.: 11 - 14.

[7] Fleiss, JL. The Design and Analysis of Clinical Experiments. New York, NY: John Wiley & Sons, 1986.

[8] Jiang, H, J Starkman, M Liu, and M Huang. “Food Nutrition Visualization on Google Glass: Design Tradeoff and Field Evaluation.” IEEE Consumer Electronics Magazine, May 2018: 21 - 31.
[9] Kaiser, MJ, et al. “Frequency of Malnutrition in Older Adults: A Multinational Perspective Using the Mini Nutritional Assessment.” Journal of the American Geriatrics Society, September 2010, 58 ed.: 1734 - 1738.

[10] Lazaro, JP, A Fides, A Navarro, and S Guillen. “Ambient Assisted Nutritional Advisor for elderly people living at home.” Proceedings IEEE Engineering in Medicine and Biology Society. 2010. 198 - 203.

[11] Luo, S, H Xia, Y Gao, JS Jin, and R Athauda. “Smart Fridges with Multimedia Capability for Better Nutrition.” International Symposium on Ubiquitous Multimedia Computing. Hobart: IEEE, 2008. 39 - 44.

[12] Maschollek, M, et al. “Multimodal activity monitoring for home rehabilitation of geriatric fracture patients—feasibility and acceptance of sensor systems in the GAL-NATARS study.” Informatic for Health and Social Care, Sep - Dec 2014, 39 ed.: 262 - 271.

[13] Milne, AC, J Potter, and A Avenell. “Protein and energy supplementation in elderly people at risk from malnutrition.” Cochrane Database Syst, 15 April 2009.

[14] Moguel, E, et al. “Monitoring Food Intake in an Aging Population.” Proceedings, 31 October 2018, 2 ed.

[15] Reščič, N, E Valenčič, E Mlinarič, KB Seljak, and M Luštrek. “Mobile nutrition monitoring for well-being.” UbiComp/ISWC ’19 Adjunct: Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers. New York, United States: Association for Computing Machinery, 2019. 1194 - 1197.

[16] Rolland, Y, et al. “Sarcopenia: Its assessment, etiology, pathogenesis, consequences and future perspectives.” The Journal of Nutrition Health and Aging, August 2008: 433 - 450.

[17] Volkert, D. “Leitlinie Enterale Ernährung der DGEM und DGG: Ernährungszustand, Energie- und Substratstoffwechsel im Alter.” Aktuel Ernahrungsmed, 2004: 190 - 197. (German)