Smart Food Tracking: Accuracy and Applicability

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ABSTRACT:
Food diaries are important tools to support the treatment of various non-communicable diseases including cardiovascular diseases and diabetes. However, maintaining food diaries can be tedious due to the large variety in food type. Additionally, location and time of food intake may vary considerably. Ubiquitous mobile technologies can be a valuable persuasive technology in this context. But how is the acceptance of people in the use of mobile technology to monitor health-related values such as food intake? Based on a questionnaire we analyze the willingness of recording health-related data by smartphone. Results show great interest, but also concerns about privacy. These concerns can be met. However, the accurate description of a meal still proves to be difficult. Most human beings judge amount by visual impression. The volume-to-energy ratio is most important for easy visual portion estimation. Therefore, a clustering of the *USDA National Nutrient Database for Standard Reference* based on volumetric reference values was performed. The accuracy of portion evaluation based on an easy volumetric reference value in a group of 28 young adults was evaluated. Finally, a software module for estimation of carbohydrate content based on one volumetric reference was implemented and the applicability was tested in a group of nine diabetic patients.

1 INTRODUCTION

36 million people per year die from non-communicable diseases (NCDs). The most widely spread NCDs, such as diabetes and cardiovascular diseases, cancer, chronic respiratory diseases and mental diseases cause 77% of the disease burden in the European region [1]. For most of these diseases nutrition is an important parameter for prevention as well as successful treatment. To implement successful interventions knowledge of a person's nutritional behavior is of great importance. Historically, paper based food diaries are used for this purpose. Keeping such food diaries can be tedious with adverse effects on data quality. Mobile technologies proved their ability to simplify the maintenance of food diaries [2]. However, the simple and accurate logging of the nutritional values of food intake still remains an area of active research.

But do people see potential in digital health data recording and which concerns exist? To address this question a questionnaire focused on pros and cons of recording digital health data is answered by 28 young adults. The results show positive expectations as well as security concerns. We believe that given these concerns can be met people are strongly interested in digital health solutions.

Nutritional values can be measured by weighting the different parts of a meal and using reference databases [3]. However, weighting is not feasible in many situations; therefore accurate visual estimation of nutritional content is of great importance. For this purpose foods have to be grouped according to their carbohydrate and kilocalorie content per volume instead of carbohydrate and kilocalorie content per weight. A clustering of the *USDA National Nutrient Database for Standard Reference* (USDA-NNDSR) [3] based on these two parameters is performed which shows that resulting food groups vary significantly from traditional categorizations of foods.

In the follow-up the accuracy of estimations of nutritional values of meals based on an easy reference object, namely a person's fist, is evaluated. As shown in previous studies many people tend to overestimate the food volume on their plate [4]. This effect is also apparent in our experiment. Nevertheless, the accuracy increases significantly when people estimate first the size of their fists with a newly developed mobile augmented reality (AR) application and in the follow-up estimate the number of fists equivalent to the amount of food on their plate.

Finally, a simple smartphone based bread unit estimation module was developed and tested in a study with 9 diabetic patients.

2 QUESTIONNAIRE: DIGITAL HEALTH MONITORING

In Table 1 the results of the questionnaire answered by a group of 42 young adults are given. The questioning was performed by using the EasyPolls website[1]. It can be deduced that most of the participants see opportunities in digital health solutions. About one third of the participants would be interested in continuous monitoring of health related quantities. This may be due to existing health issues or a general interest in tracking health related parameters [5]. None of the participants would like to publish health data on the internet without additional constraints. More than two third of the participants would never publish health related data on the internet and a similar amount thinks continuous logging of health related data is potentially dangerous. Concerning the question if all medical data deserves protection the answers are almost balanced.

Table 1. Questionnaire relating to digital health and health related data.

Question	Yes	Depends	No	n
Does digital health provide opportunities to target diseases in a better way?	97%	n/a	3%	38
Do digital health solutions provide an opportunity to economic problems of current health care systems?	68%	n/a	32%	38
Can digital health solutions increase personal freedom?	76%	n/a	24%	38
Would you like to measure health related quantities from your body continuously?	38%	n/a	62%	42
Would you like to publish your health related data on the internet?	0%	28%	72%	40
Is the continuous measurement of health related data potentially dangerous?	69%	n/a	31%	42
Do ALL medical data deserve protection?	53%	n/a	47%	38

3 FOOD CATEGORIZATION

Nutrition has a strong influence on almost all health aspects. One important question is how to categorize different foods in order to give recommendations for the proposed amount of intake of different food groups. Current classifications are built mostly on expert knowledge. These systems therefore lack deterministic rules on how the groups are defined. From the USDA-NNDSR the carbohydrates and kilocalories per volume are computed for 1801 different foods. The carbohydrate and kilocalories per volume are used as parameters as human beings tend to judge amounts based on visual impression.

To be able to generate a categorization of different foods, the OPTICS clustering algorithm [6] is applied to the data (see Figure 1 for the associated reachability plot). Valleys in the reachability plot represent clusters in the associated data. Clusters are defined automatically using a self-developed algorithm.

The entries in the highlighted cluster consist of canned soups, canned vegetables, cottage cheese, baby foods and snacks. All these foods have a very similar carbohydrate- and kilocalorie-to-volume-ratio; nevertheless, in existing food categorizations they mostly appear in different categories.

[1]www.easypolls.net

Foods in the dark orange region of the scatter plot contain a relatively large amount of fat and/or protein as their carbohydrate content accounts for less than half of their kilocalorie content. For example, most points in lower right corner represent different types of oils.

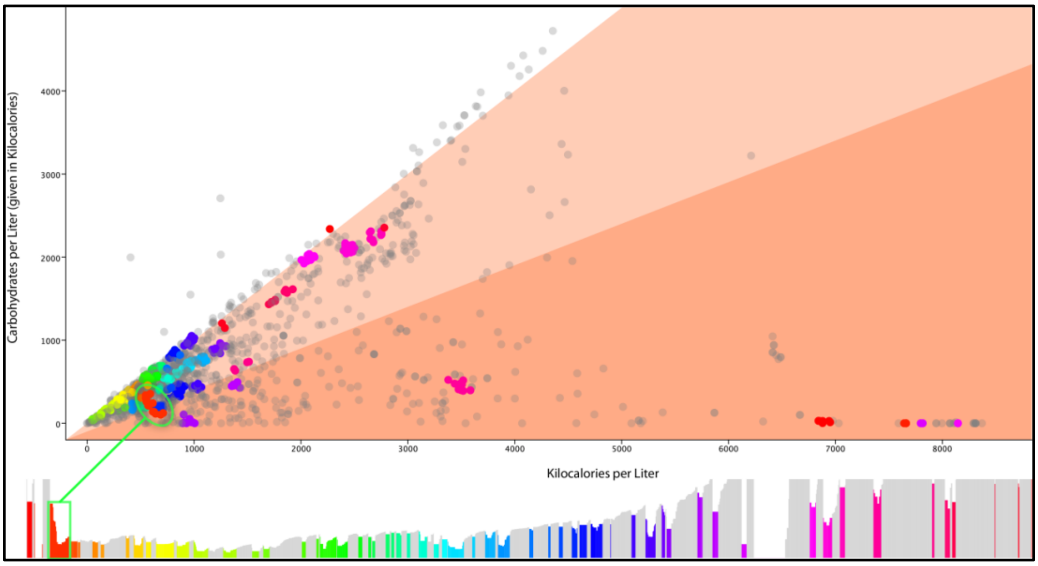

Figure 1. Scatter plot and reachability plot of foods from the USDA-NNDSR according to their carbohydrate- and kilocalorie-to-volume ratios

4 MEASURING FIST SIZE AND ESTIMATION OF FOOD VOLUME IN FISTS

The goal of this study was to evaluate the accuracy of visual volume estimation in a group of 28 people (3 females and 25 males). Here the size of one's fist is used to estimate the amount of food on a plate. Therefore the size of the participant's fists has to be measured which is performed in two ways. Firstly, the fists of the participants are submerged under water in a measurement container such that the head of the ulna just stays out of the water. The difference in milliliters defines the respective volume. Secondly, the fist-size is measured using a mobile AR application (see Figure 3a). In the follow-up the 28 participants estimate the volume of three portions of rice. The three portions were prepared to have volumes of 200, 300 and 400 cm^3, respectively.

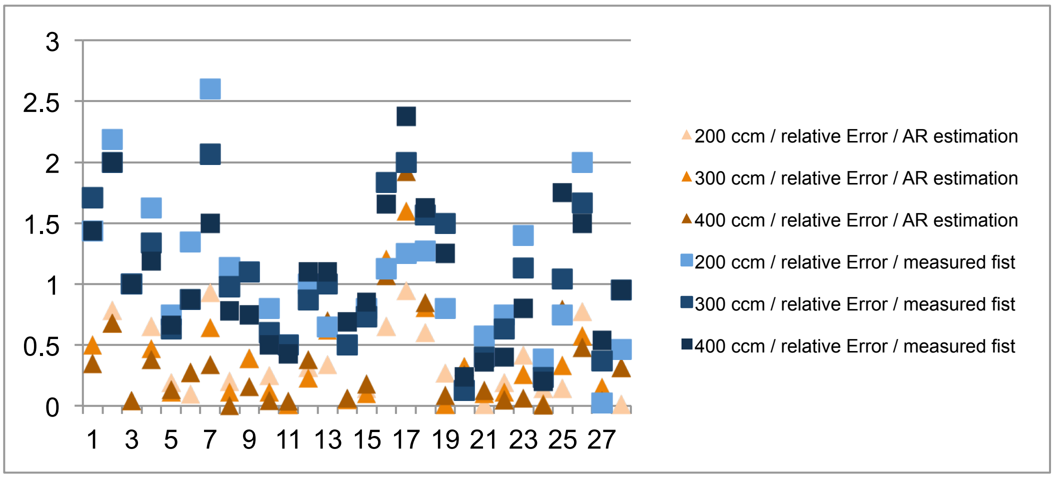

Figure 2. Relative error of volume estimations based on fist measurements using the mobile AR application (orange) versus using water displacement (blue).

The relative error of the estimations is substantially decreased by using the AR-based fist measurement (see Figure 2). Over-estimation of the volume of food relates to underestimation of the volume of the fist. The reason for the significantly better performance of the AR-based estimation relies most probably on the repetition of the underestimation of the size of the fist in both the AR-based measurement as well as the estimation of the number of fists equivalent to the presented amount of food.

5 USER STUDY WITH DIABETIC PATIENTS

Patients treated for diabetes have to estimate the amount of carbohydrate intake to be able to calculate the required insulin dosage. Reference tables to calculate the amount of carbohydrates in different foods rely mostly on weight measures. Using a scale is not always feasible; therefore estimation of carbohydrates by visual inspection is an important ability. In a small experiment we measured volume to weight ratios for common carbohydrate rich foods (see Table 2). The associated errors in bread units (ε) shown in Table 2 are in general below ½ bread unit. Bread units are calculated by using the standard convention to divide the weight of cooked noodles or rice by 50, the weight of cooked potatoes by 70 and the weight of french fries by 33 (see McDonalds™ nutrition facts[2]). According to personal communication with diabetologists accuracy below ½ bread unit is rarely medical relevant. Therefore in general the volume to carbohydrate conversion provides sufficient accuracy.

(a) (b)

Figure 3. a) Estimation of fist volumes using the mobile AR application. b) Estimation of bread units based on fist volume.

In a study nine diabetic patients were provided with a smartphone application to estimate bread units based on the equivalent in fists for the duration of two week (see Figure 3b). The participants could estimate the amount bread units of their food and subsequently edit the proposed value in case it seemed incorrect. One participant used the estimation module regularly over the whole time of the study. Additionally, this participant accepted all estimations without further correction which leads us to the conclusion that the results of the estimation procedure were satisfactory. The reason for the low interest in the automatic food estimation procedure may be found in the fact that all of the participants were skilled in measuring or estimating bread units by other means.

[2] http://www.mcdonalds.at/#/produkte/

Table 2. Volume-to-weight-ratios (δ) of different types of cooked carbohydrate rich foods. Values were calculated based on 3 portions with 100g, 200g and 300g, respectively. The average of the δs is then used for the error estimations in bread units (ε).

	δ_{100g}	δ_{200g}	δ_{300g}	μ_{δ}	ε_{100g}	ε_{200g}	ε_{100g}
Spaghetti	0.33	0.40	0.40	0.38	0.27	0.22	0.33
Pene Rigate	0.40	0.42	0.43	0.42	0.08	0.04	0.17
Fusili	0.33	0.33	0.40	0.36	0.13	0.27	0.67
Pipe Rigate	0.40	0.40	0.40	0.40	0.00	0.00	0.00
Potatoes	0.50	0.50	0.60	0.53	0.10	0.19	0.48
Rice	0.50	0.57	0.60	0.56	0.23	0.10	0.43
French Fries	0.27	0.27	0.29	0.27	0.07	0.14	0.40

6 DISCUSSION

Logging nutritional values of meals is an important but most often complicated task. Based on our work we propose to define a new categorization of food with respect to on energy per volume. With the used of easy reference objects it will be possible to increase the accuracy of nutritional value estimations. AR-based smartphone applications can assist in estimation of the volume of the reference object, thereby implicitly taking the individual perception into account. A study with nine diabetic patients lead us to the conclusion, that these smartphone based estimation aids are of most use to people who are not yet trained in estimation techniques.

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