Dietary Intake Assessment using Integrated Sensors and Software

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ABSTRACT

The area of dietary assessment is becoming increasingly important as obesity rates soar, but valid measurement of the food intake in free-living persons is extraordinarily challenging. Traditional paper-based dietary assessment methods have limitations due to bias, user burden and cost, and therefore improved methods are needed to address important hypotheses related to diet and health. In this paper, we will describe the progress of our mobile Diet Data Recorder System (DDRS), where an electronic device is used for objective measurement on dietary intake in real time and at moderate cost. The DDRS consists of (1) a mobile device that integrates a smartphone and an integrated laser package, (2) software on the smartphone for data collection and laser control, (3) an algorithm to process acquired data for food volume estimation, which is the largest source of error in calculating dietary intake, and (4) database and interface for data storage and management. The estimated food volume, together with direct entries of food questionnaires and voice recordings, could provide dietitians and nutritional epidemiologists with more complete food description and more accurate food portion sizes. In this paper, we will describe the system design of DDRS and initial results of dietary assessment.

Keywords: Dietary intake assessment, smartphone, integrated sensor, image processing, volume estimation, 3D reconstruction.

1. INTRODUCTION

Dietary intake information is valuable for understanding the relationship between diet and health, which is becoming increasingly important due to soaring obesity rates. Over two-thirds of the adult U.S. population are either overweight or obese [1]. Overweight and obesity are risk factors for cancer, diabetes, cardiovascular disease, high blood pressure, and other health problems [2-4]. The annual number of deaths attributed to obesity is estimated to be as high as 400,000 in the United States alone [5]. There is no single cause of overweight and obesity; therefore, no single method exists for preventing or treating these conditions. Treatment may include a combination of diet, exercise, behavior modification, weight-loss drugs, or even bariatric surgery, in some cases of extreme obesity. The annual estimated medical costs of obesity in the US were as high as \$147 billion in 2008, or almost 10% of the total medical spending for that year [6, 7].

Obtaining valid measurements of dietary intake for free-living persons is one of the most challenging problems in nutrient studies [8]. Currently, doubly labeled water (DLW) is considered the gold standard for measuring food intake in free-living conditions, but DLW has important limitations including its high cost and lack of real-time applicability. Alternative methods for measuring food consumption are often based on participants' reports, including interviewer-administered 24-hour dietary recalls (24HR), paper-based food diaries, and food frequency questionnaires (FFQ). Since these methods require participants to remember both the foods consumed, as well as estimate the portion size, they all have limitations due to bias, error, participant underreporting, and staff and participant burden and cost. Studies have shown that these methods underestimate food intake by 37% or more [9-11]. Particularly, 24HR and food diaries carry very high participant burden and high costs for data collection, making them generally unfeasible for use in large epidemiologic studies. On the other hand, although FFQs have been widely used for dietary assessment in large cohort studies due to their ease of administration and low cost, they cannot be used to measure the absolute dietary intake [12]. Therefore, it is desirable to develop better methods for measuring the amount of dietary intake.

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If we are to obtain objective, real-time measures of dietary intake in large studies, we will need alternatives to the interviewer-administered 24HR and the paper-based, multiple-day food diary. Work is currently underway at the National Cancer Institute (NCI) to develop a computer-administered 24-hour recall, which has enormous potential to lower the costs of recall administration and analysis. The goal of our study focuses on developing a more accurate and less burdensome alternative to the paper-based food diaries. Through the use of advanced technology like miniaturized sensors, data recorders, and image processing algorithms, it should now be possible to collect more objective data on food consumption in real time and at moderate cost. In our study, we develop a Dietary Data Recorder System (DDRS), which is an integrated sensor with corresponding software to record dietary intake in clinical and epidemiologic studies. Figure 1 illustrates the overview of DDRS. First, the participant gets the mobile device from the nutritionist, and uses it to record his/her food intakes. Then, the data are uploaded to the server, processed, and stored in a database. Finally, nutritionists perform the analysis and collect useful information, where the Nutrition Data System for Research is used to convert food items to nutrient components [13].



Figure 1. DDRS overview.

The paper is organized as follows. Section 2 reviews the previous related work. Section 3 describes the system design of DDRS, including the mobile device, software for data collection, algorithms to process the acquired data, and database interface. Section 4 presents initial results of dietary assessment experiments. This is followed by the conclusion and future work description in Section 5.

2. RELATED WORK

In this section, we review previous studies on dietary intake assessment and image-based 3D reconstruction. Both the traditional and recent electronic methods are presented, and the advantages and limitations of the existing dietary assessment methods are discussed. The background reviews demonstrate the significance of the DDRS, as well as the foundation and rapid research progress of the dietary intake assessment.

2.1 Traditional dietary assessment methods

The traditional dietary assessments, including the doubly labeled water (DLW) and self-report methods, are well established and have been widely used in nutrient studies. The DLW method was a major breakthrough, which allowed researchers to obtain reliable and accurate estimates of habitual energy expenditure for humans under free-living conditions [14]. This method was originally developed in the early 1950s to estimate the energy output of small animals [15]. During the first ten years of its use in humans, the DLW method was extensively validated and is now considered the "gold standard" for the measurement of total energy expenditure (TEE) of humans. Nevertheless, the DLW method is expensive as it requires the use of sophisticated equipment to estimate the concentration of the isotope, which itself is also expensive and in short supply. In addition, since it takes at least several days to screen the water's movement through the body, DLW can neither provide clinicians with frequently accurate estimation of food intake, nor record the types of consumed foods.

The majority of popular alternatives to DLW are based on participants self-reporting, including 24-hour recall (24HR), food records, and food frequency questionnaires (FFQs). In the 24HR method, foods and amounts consumed during the previous day (or 24 hours) are recalled from memory, with the aid of an interviewer who has been trained in collecting dietary information. The primary strengths of dietary recalls are that trained interviewers can probe for details about food ingredients and preparation, and that the data collection itself cannot affect past behavior. The primary weaknesses are that participants may forget foods, report foods not eaten, or inaccurately report ingredients, food preparation methods, and portion sizes [16]. Another standard approach is the food diary or food record method. The primary strengths of the food diary are that it does not rely on memory, provided that foods are recorded in real-time and the portions can be weighed or measured. The primary weakness is that the act of keeping a diary can influence dietary behavior; therefore, not providing accurate indicators of standard behavior [16]. Both 24HR and food diary methods carry very high participant burden and have high data collection costs, making them generally unfeasible for use in large epidemiologic studies. Thus, over the past 25 years, virtually all epidemiologists conducting large studies that require dietary assessment have used list-based methods such as the FFQ. There is a large degree of controversy in the epidemiologic and human nutrition research communities about whether FFQs are sufficiently valid to provide strong evidence about diet and disease risk [17-19]. It is incontrovertible, however, that FFQs cannot be used to measure the absolute intakes of energy or macronutrients [12], which are critical in studies of obesity or food-based exposures to environmental contaminants. Moreover, FFQs cannot adequately capture the multiple, diverse and complex mix of cuisines consumed by many Americans [20].

2.2 Electronic food diary based on images

Digital images can measure accurate portion size of foods in laboratory settings, where the camera, distance from camera to object, angle from lens to object, etc. can be rigorously standardized [21]. Image-based systems have already been used in the food industry, where the size and shape can be used to sort fruits and vegetables into size groups. Different methods of 3D reconstruction have been deployed to capture food volume, including stereovision [50], shape from silhouette [22], and active triangulation [23]. Systems for measuring horticultural product size can be found in [24]. However, similar systems cannot be used for free living persons due to the portability problem.

With the advent and popularity of small handheld devices, several devices, including CalorieKing, BalanceLog, and DietMatePro, have been developed for direct entry of foods [25]. These systems simplify data collection and analysis for researchers and some incorporate date/time stamps, reminders to record meals and queries to minimize invalid entries. However, high literacy and participant motivation are required, and similar to paper records, portion sizes are frequently reported inaccurately [26, 27]. Integrated approaches are more promising, which combine food images with food descriptions. One example is the Multimedia Diet Record (MMDR), which combines images from a 35 mm camera, food descriptions recorded on a micro cassette recorder, and written documentation, such as recipes and food package labels [28]. Unfortunately, the MMDR is burdensome to maintain and, similar to other self-report measures, total energy intake is under-reported by about 24%. In contrast, a much better example of the potential of using integrated sensor technology is the Wellnavi, a hand-held device that captures video images and digitized hand-written food descriptions, provides prompts, administers short questionnaires on food practices, and transmits data via wireless networks [29]. Using the Wellnavi is still somewhat awkward, because images must be captured at a 45° angle with a ruler-like stylus placed near the food and users must write food descriptions on the digital screen. Registered dietitians then used the images to estimate the food consumed. Although this system did not actually perform 3D reconstruction, it did utilize the stylus as a reference.

Later, several systems based on 3D reconstruction were proposed with the development of computer vision algorithms. In [30], participants were trained to take a food image while a reference card with printed rectangles was placed near the food. Then their system computed the food area, and assumed the linear proportionality between the area and the volume. However, this assumption is not valid under many situations, where different shapes of food, different angles for camera positions, etc. can deviate from the methodology. In [31], participants laid a card with colored grids close to the food, and took a single image by using an iPhone. The reference card was of a credit-card size for better portability. Their algorithm used several shape templates for regular food, estimated the shape parameters from the single image and the reference card, and computed the volume from these parameters. For irregular food shapes, it used the closest template for approximation. In [32], a grid reference was also placed near the food, but multiple images were captured and stereo matching was applied. 3D reconstruction can be performed for food with rich texture, but may have limitation for textureless regions. In [33], they designed a wearable system by themselves rather than an off-the-shelf cell phone or PDA. This system also used shape templates, but required plate with a fixed size rather than a reference card. All the systems mentioned above are based on passive reconstruction methods and the scale is determined by fiducial markers, which are separated from the camera.

3. SYSTEM DESIGN

The DDRS is composed of four major components: (1) a mobile device that integrates a smartphone and a laser package, (2) software on the smartphone for data collection and laser control, (3) an algorithm to process acquired data for food volume estimation, and (4) database and web interface for data storage, management and retrieval. The key innovative feature of DDRS is a mobile structured light system (MSLS) that contains a camera and a laser projector. By using MSLS, the DDRS could calculate food volume without using any additional fiducial markers. More information about the MSLS could be found in [34, 35]. In this section, we will focus on the system design of DDRS and introduce all four components.

3.1 Mobile device

The mobile device of our DDRS consists of a mobile phone, a laser module and a circuit module bridging the phone and laser. All of the components are mounted in a small plastic housing, so participants can use it in their daily life. Figure 2 shows the device in the customized housing. The housing is designed by 3D computer-aided design (CAD) software SolidWorks, and printed by a Dimension 3D printer using black acrylonitrile butadiene styrene (ABS) plastic materials. It provides a tight fit for all components so that the distance and angle between the camera and laser are fixed. The bottom part in Figure 2 is the smartphone sitting in the housing, the top part under the logo is the laser generator, and the controlling circuit is lying under the phone inside the housing. The housing is slightly larger than the smartphone itself, and can fit in the participant's pocket.



Figure 2. The mobile device of DDRS.

Laser module

The laser module is selected as the light source in the mobile device since it is compact, easy to control, and has fast response to the controlling signal. Some high-end laser modules that generate structured light patterns may cost several hundred dollars, which are even more expensive than the smartphone. To reduce the cost, we constructed the laser module by using a cross laser pointer and a diffraction grating from NovaLasers. The diffraction grating in our system is called Mega Matrix, which is not uniform but has a brighter center. The cross from the laser pointer interacts with the gratings, resulting in a rectangular grid with brighter central lines. The index of each line in the grid can be determined by counting how far it is from the center. As a result, a structured light grid with coded information of all lines is established for generating structured light.

Circuit module

An electronic circuit module is designed to provide an interface between the phone and laser. The module precisely turns the laser on and off in response to activation commands from the mobile application on the smartphone, as well as connects the laser to a battery power source. Communication between the phone and circuit is accomplished through Bluetooth, the mobile application utilizes the existing Bluetooth functionality of the smartphone, and a Bluetooth module is integrated into the circuit. To activate the laser in response to Bluetooth module output, a simple switching network is utilized, characterized by discrete MOSFET transistors and carbon film resistors.

The circuit connects to an external 3.7 V battery to provide power to the laser and Bluetooth module, and has been designed to allow the user to easily recharge the battery power source. The interface for the recharging functionality is a PCB mountable Mini USB connector, which can be readily connected to a variety of external power sources. Furthermore, the Bluetooth module drains substantial power during idle operation. Such constant power drain can deplete the battery quickly, resulting in the need for frequent recharge sessions. To extend periods between recharging, the module includes a switch to turn power to the Bluetooth on or off. This switch is to be manually operated by the user, in accordance to command prompts given through the software user interface. There are two notches for the connector and switch in the plastic housing.

To keep the module compact and durable, the electronic circuit is entirely integrated into a PCB. The small size of the module, roughly 3 cm x 5 cm x 1 cm, allows it to be included into the system carriage without the need of any extra external design considerations. Overall, the circuit module has shown to be durable and reliable over extended testing periods. Figure 3 shows a detailed image of the PCB with all the elements.



Figure 3. The circuit module in the mobile device.

3.2 Software on the smartphone

Current smartphones are suitable instruments for electronic food diaries as they provide high resolution cameras, large storage size, high-speed network access, moderate computation power, and programmability. We developed a mobile application for collecting data and controlling the laser module via the circuit module. The data collection follows the procedure designed by dietitians in Fred Hutchinson Cancer Research Center, and requires voice and video collection additional to the standard questions in the paper-based methods. During the video collection, we slowly move the camera around a food, stabilize at several positions, and collect video sequence instead of a single image to cover all sides of the food. By sending out a Bluetooth signal to the circuit, the laser is turned on and off during the video collection, resulting in video frames with and without laser grids alternately. Since the motion between two adjacent frames is small, non-

grid images can assist in the analysis of the grid images. The mobile application was developed in JAVA on the Android operating system. Google Nexus One was chosen as the smartphone for development, but the application could also be used on other Android-based platforms. Besides the camera, Nexus One is also equipped with a 3-axis accelerometer and a digital compass, whose data can also be used in our reconstruction process.

Besides controlling the laser module, the software mainly collects two kinds of data, the answers to survey questions and the meal data. At the beginning and in the end of a study, the user needs to answer a series of survey questions, such as eating habits. In the middle of the study, the user needs to record the intake of meals. For each meal, the user needs to answer questions like time and places, and take video, audio, phone and/or barcode of the food. After data collection, the user could review the data, and edit on it if necessary. Figure 4 shows several screenshots of the mobile application. All the data collected are stored into XML files, and will be sent to the database for further analysis.



Figure 4. Screenshots for the mobile application.

3.3 Data processing algorithms

By using the data collection device and software, we are able to collect image, video, audio and/or text descriptions of the foods. On the other hand, the amount of foods is estimated by the data processing algorithm in our system. Since the smartphone has only moderate computational power, it is suitable for data collection but not for volume estimation. Furthermore, some user interaction may be necessary during estimation process. Therefore, acquired grid videos are transferred to a server for further processing. As mentioned in Section 3.2, a video sequence is extracted into pairs of consecutive frames, one image with the laser grid projected and one without. Currently we manually select several pairs of images whose motion is small, and later we will automate it by detecting motion using accelerometer data and images from Nexus One. The steps to process the selected image pairs and generate depth maps are as follows: (1) segment the food region from the background; (2) extract laser grid lines on the food from the image; (3) extract intersection points in the grids; (4) identify the central point of the grid; and (5) create depth maps from a calibrated SLS. After depth maps are generated for all image pairs, they can be registered to create the 3D model.

Food segmentation

The food region should be segmented from its background. However, segmentation on grid images may suffer. Foods of free-living participants are not on a turnable stand as it is for common laser scanners, and may be close to the background objects. The boundary information could be destroyed and common segmentation algorithms may fail. Therefore, we applied segmentation on non-grid images, and used the result for image pairs. To support food segmentation under complex scenes, a video segmentation scheme is extended from the Edge Detection and Image Segmentation (EDISON) [36] and Maximal Similarity based Region Merging (MSRM) [37].

Grid line extraction

The laser grid lines should be extracted from the image pair for the following steps in our algorithm. The non-grid image is subtracted from the grid one. After transforming the subtraction image into grayscale, a Gaussian filter is applied and subtracted from the original grayscale image. The result then is transformed into a binary image, where morphological processes can be applied. For our application, isolated pixels are removed, a horizontal and vertical

structuring element is used to perform morphological closing, and then the lines are thinned to form a skeleton. Finally, the grid skeleton is stored for later processing.

Intersection extraction

To generate a depth map, the intersection points in the grids need to be extracted from the grid. First, the intersection candidates were located by finding the branch points in the grid skeleton. Using the candidate points obtained, we further filtered the results by obtaining the perimeter of a window around each candidate from the skeleton image. The window size can be determined by roughly estimating the density of the candidates. If the window perimeter cuts across the grid skeleton at 4 spots, the candidate is considered to be an actual intersection [38]. Figure 5 shows comparison between valid and invalid intersections although both of them have local branches. The temporary results are further filtered by checking the Euclidean distance of each intersection to another. If the distance is less than a certain threshold, the two intersection locations are combined and averaged.



Figure 5. Valid and invalid intersections.

Central point identification

The central point in a grid needs to be identified since it is the reference of other intersection points. Central lines are much brighter than the other ones in our SLS, so the grayscale intensity is used to locate the central point. Using the similar process as intersection extraction, the perimeter of a window can be created around each intersection. The perimeter will cut across the grid skeleton at 4 positions. The central point has high intensities at all 4 positions, other intersection points on the central lines have high intensities at only 2 positions and low intensities at the other two, and points off central lines have low-intensity at all 4 positions. After this process, the central point of a laser grid is differentiated from others.

Depth map creation

With the extracted intersections and the identified central point, a depth map could be created from a pair of images. In a calibrated system, if we know the distance between the camera and laser, the angle for a laser beam, and the angle of a pixel in the image, we can calculate the depth by triangulation. For each intersection point in the image, we should know the pixel position in the image and the index that represents its corresponding laser beam. Since our SLS would work under complex circumstances, some intersections on the food may not be detected. The requirement of our SLS is that the central point is projected on the food and can be detected, and depth maps can be created even if some intersections are missing. To achieve this, we proposed an adaptive Splitting Cell Algorithm (SCA), which is a modified version of SCA [39, 40].

The SCA contains two steps, calibration and depth map creation. For calibration, we acquire a series of images in a valid range of depths from the camera to a plane. The intersection points in all planar images are displayed in a single calibration image, where line segments are formed. Each line segment is corresponding to one intersection, and illustrates how this intersection will move while the depths from the camera to an object change. This calibration image represents all information for a fixed SLS, so we do not need to calibrate for the distance and angle between the camera and laser. Once calibration is finished, depth map creation is straightforward. For an intersection in an image, it is projected onto the line segment closest to it. Then the depth of this intersection is estimated by using the ratio in the line segment, and the index of its corresponding laser beam is also determined. More details of SCA can be found in [40].

We have improved the SCA for our system. In the original SCA, a calibration image is segmented into rectangular regions. Each rectangle is corresponding to one line segment, and there should be no overlap between adjacent rectangles. As a result, the valid range of depth is limited for this non-overlapping requirement. However, we can increase the valid range of our SLS based on two assumptions: the central point of the laser grid is always on the food, and common foods are not of very large volume. Based on these two assumptions, we proposed our adaptive SCA (aSCA) as follows: (1) acquire planar images from a large range of depths, which will cause overlapping in original SCA; (2) generate a temporary calibration image that only contains the line segment corresponding to the central point; (3) estimate the depth of central point from the line segment; (4) select a portion of planar images that are within a

certain range from the central depth; (5) generate a final calibration image that contains line segments of all intersection points; and (6) create the depth map using SCA. In our aSCA, the valid range is adaptively determined from the depth of central point, so depth map creation can be better supported than the SCA. After depth maps are created, they can be registered to generate the 3D model.

3.4 Database and web interface

The information management system is designed using a MySQL database with a DRUPAL-powered web front-end interface. The core functionality of the system is to parse data from the mobile devices (XML files), store the data in the appropriate tables, and generate consolidated reports as needed. The input consists of structured text data, set of images, audio files, video files, and data from accelerometers. In addition to raw data the schema stores metadata about the devices and anonymous participant information. It also includes various roles to support data input and retrieval for analytics and reporting.

Figure 6 illustrates the DRUPAL-powered web front-end interface of DDRS. DRUPAL is a popular open-source content management platform, offering our group control over the functionality of the system and reducing the amount of effort required to develop it. DRUPAL-powered sites can be configured to be viewable from mobile phones, making our output reporting system effective everywhere. The tool integrates with the Tableau-powered report generator to serve as our output reporting system to provide data to different user groups. Currently, the reporting system provides data to two different sets of users: (1) clinicians and researchers who can view aggregate data, and (2) device users (e.g., patients and study participants) who can review their own data. Clinicians and researchers will have the ability to upload, edit, and review data, while device users will have the ability to upload and review data. Both user sets will receive email notifications of reports.



Figure 6. The web frontend interface of the DDRS.

4. RESULTS

In this section we will show current status and results of our system. Currently, we have completed the design of the mobile device, and the implementation of software on the Android phone. We have also developed most components in the data processing and management system, but an integration of all the programs is still yet to be developed. We have developed several functional prototypes of the data collection device, three of which have undergone feasibility tests in pilot clinical studies.

As mentioned in Section 3, our mobile device projects flashing laser grids on the food, and acquires video frames with and without laser grids. The Bluetooth trigger and video sequence are synchronized, so a flag from a timestamp indicates whether a frame is with grids or not. In the acquired video, food is segmented from the background in non-grid frames by using a video extension of MSRM [37]. Figure 7 shows how a sandwich is segmented from its complex background by some simple user input, and how a muffin that collected in our lab setting is segmented from a dark background.



Figure 7. Food segmentation from a scene.

Figure 8 shows a pair of images with and without grids on a muffin. The grid quality is not perfect since the laser cross from the generator is not well focused. We are planning to replace it with a better laser generator. After that, the laser grid lines and intersection are extracted, and central points are identified. Figure 9 illustrates the identified center point in one image.



Figure 8. A pair of images with and without laser grids.



Figure 9. Identified center point in one image.

Depth maps can be created with the proposed aSCA. To verify our aSCA, we developed simulation for SLS, which uses the camera model, laser model, and the distance and angle between the camera and laser as inputs. The error between the actual and computed distance is less than 1% of the distance. It is caused by the quantization for pixel locations. We also tested the aSCA with the image collected by our SLS. The typical error is less than 2% but there some outliers. The reason for this is the unfocused laser lines. Once the depth maps from all directions are created, they can be registered for a 3D model.

5. CONCLUSIONS AND FUTURE WORK

In this paper, we have presented the Diet Data Recording System (DDRS), which includes integrated sensors and software for dietary intake assessment. We have designed hardware and software for data collection, algorithm to process the structured light images, and database and web interfaces to manage the dietary data. The proposed mobile device has a slightly larger form-factor than a smartphone, so it is portable for free-living participants. A pilot study has been conducted to test the feasibility of our system. Future work includes automating the data processing pipeline,

integrating the various components seamlessly as an entire system, and improving the DDRS with the feedback from the clinical study.

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