The Kunming CalFit Study: Modeling Dietary Behavioral Patterns Using Smartphone Data

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Abstract— **Human behavioral interventions aimed at improving health can benefit from objective wearable sensor data and mathematical models. Smartphone-based sensing is particularly practical for monitoring behavioral patterns because smartphones are fairly common, are carried by individuals throughout their daily lives, offer a variety of sensing modalities, and can facilitate various forms of user feedback for intervention studies. We describe our findings from a smartphone-based study, in which an Android-based application we developed called CalFit was used to collect information related to young adults' dietary behaviors. In addition to monitoring dietary patterns, we were interested in understanding contextual factors related to when and where an individual eats, as well as how their dietary intake relates to physical activity (which creates energy demand) and psychosocial stress. 12 participants were asked to use CalFit to record videos of their meals over two 1-week periods, which were translated into nutrient intake by trained dietitians. During this same period, triaxial accelerometry was used to assess each subject's energy expenditure, and GPS was used to record time-location patterns. Ecological momentary assessment was also used to prompt subjects to respond to questions on their phone about their psychological state. The GPS data were processed through a web service we developed called Foodscoremap that is based on the Google Places API to characterize food environments that subjects were exposed to, which may explain and influence dietary patterns. Furthermore, we describe a modeling framework that incorporates all of these information to dynamically infer behavioral patterns that may be used for future intervention studies.**

I. INTRODUCTION

A number of conceptual theories govern human behavior change [1, 2], however, relatively few behavioral intervention studies incorporate continuous objective measures of behavior using sensors, or translate concepts into mathematical formalism, such that behavioral patterns may be robustly predicted, and interventions upon these behaviors can be replicated. Wearable sensors provide new opportunities to measure behaviors as they change. Smartphone-based sensing is particularly practical for monitoring behavioral patterns because, with the exception of perhaps young children and impoverished populations, smartphones are fairly common personal computing devices that are carried by a large number of individuals throughout their daily lives, offer a variety of sensing modalities, and can facilitate various forms of user feedback for intervention studies. With the goal of informing epidemiologic, wellness and obesity intervention studies, we developed the CalFit smartphone application, which measures multiple aspects of human behavior. We describe (1) the CalFit system, (2) findings from a study of young adults conducted in Kunming, China, and (3) a temporal model that integrates data from the study.

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II. CALFIT SYSTEM

The CalFit system consists of a software application that runs on Android mobile phones, which collects sensor data (triaxial accelerometry, GPS, videos), and a web service called Foodscoremap that is used to process some of the GPS data. The system has been tested and deployed on the Samsung Galaxy Y phone. Because this particularly study was conducted in China, the user interface of the app was translated to Chinese.

A. *Energy Expenditure from Mobile Phone Accelerometry*

A number of smartphone apps exist for tracking exercise, including Argus, Endomondo, Fitbit, Map My Fitness, and Moves, to name a few – some of which work alone as standalone apps, while others integrate data from other wearable devices. We developed our own triaxial accelerometer-based energy expenditure algorithm for CalFit that first applies a sensor orientation algorithm by determining the time-averaged acceleration vector as the vertical direction (i.e. the gravity vector), and second, by integrating accelerometry *counts* in the vertical and horizontal directions at 10 Hz [3, 4]. Using a generalized non-linear model, vertical and horizontal counts are used to estimate energy expenditure in units of kcal/min. The CalFit algorithm was validated in the laboratory against the Cosmed, and in free-living studies against the Actigraph [5]. The data are time-stamped and stored on the phone.

B. *Dietary Intake from Mobile Phone Videos*

Previous studies have attempted to automate the classification of food from photos and videos [6, 7]. Most of these studies have focused on only a few food items, and require considerable classification training, making such

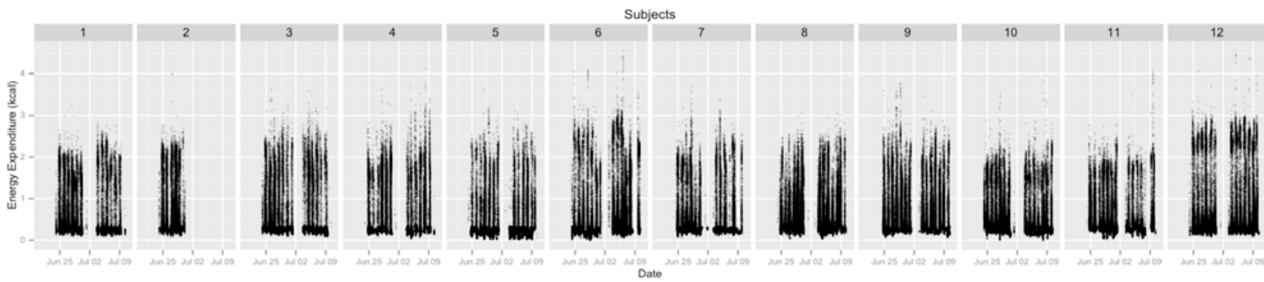

Figure 1. Each study participant's energy expenditure timeseries

approaches less feasible for real-world studies. For CalFit, we combined the benefits of video technology with human intelligence. Users are instructed to record smartphone videos of each of their meals. As they record a video, they provide voice annotation of the contents and portion sizes of the meal. These time-stamped videos are later reviewed by trained dietitians, so that the meals can be translated into nutrient contents (e.g. caloric intake, macro and micronutrients, and portion sizes of specific food groups). The use of dietitians, while costly, is feasible for a few days of monitoring to understand dietary patterns, as part of a more comprehensive personalized behavioral intervention or Health Coaching strategy.

Figure 2. Example of a meal captured on video

C. Ecological Momentary Assessment (EMA)

EMA is useful strategy for measuring psychological variables that change relatively frequently [8]. By occasionally prompting subjects to answer questions on their mobile phones, we may better understand changing psychological states *in the moment* rather than asking people to retrospectively recall these changes. The CalFit EMA for this study was triggered by the user each time they record a meal. After recording a meal, a timer is set to ask the questions again 1.5 hours after their meal, along for before/after comparisons of emotional state for each meal. The questions we asked included: *Are you about to eat? How happy are you feeling? How tired are you? Who are you eating with?* The responses to these questions are time-stamped and stored on the phone.

D. Time-location Activity and Foodscoremap

Time-location patterns were tracked using GPS. To conserve battery life for all-day monitoring, the GPS was duty cycled to obtain a measurement once every 10 seconds. After data collection, GPS coordinates were submitted to a web service we created called Foodscoremap, which uses the Google Places API to search for the number of food-related establishments (e.g. restaurants, convenience stores) within a specified radius (0.6 km) around locations where individuals spent more than 10 minutes of time.

Figure 3. Map of food environment exposure

III. THE KUNMING STUDY OF YOUNG ADULTS

Kunming is the capital city of Yunnan province, which is located in southwest China. The city has been undergoing rapid urbanization and environmental change, including the introduction of western-style food establishments. According to epidemiological studies conducted in Kunming in 2008, it was estimated that 26% of the adults in Kunming are overweight [9].

With approval from the UC Berkeley IRB, and informed consent, the CalFit smartphone system was deployed in a study of 12 young adults aged 18 to 31 years, recruited through word of mouth from Kunming Medical University students and their friends. Participants were trained on how to use CalFit. They were also trained to estimate portion sizes of common foods. They were instructed to carry the smartphone in a pouch on their waist during waking hours for two 1-week periods.

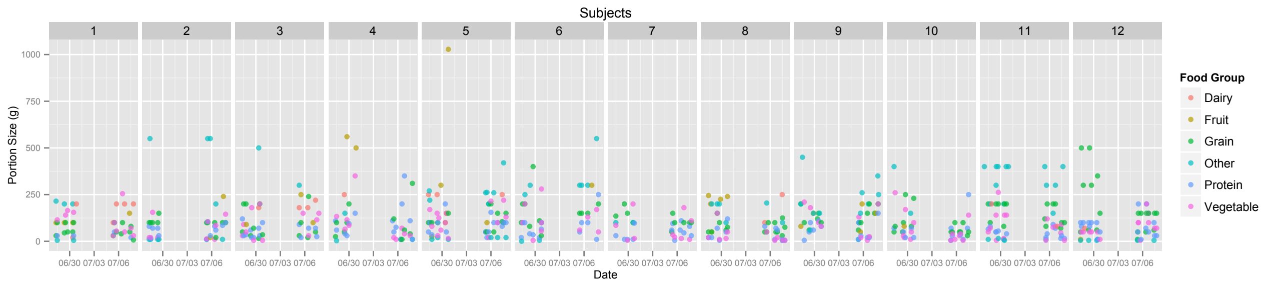

Figure 4. Each study participant's diet timeseries showing portion sizes for different food groups

A. *Study Results*

CalFit monitoring data from the study are illustrated in figures 1-4. Figure 1 illustrates the cyclical patterns of each person's daily activities, with no energy expenditure during nighttime hours, and variations in the intensity of expenditure between days for individuals, and differences between individuals. Figure 3 illustrates the results of processing the GPS data to identify locations in which individuals spent stationary time, and were potentially exposed to food establishments. Figure 2 illustrates one snapshot of one of the subject's voice-annotated videos, from which dietitians coded the contents of a meal. Figure 4 illustrates the differences between subjects in their dietary patterns. An enlargement of subject 1's data is shown in Figure 5. For some individuals, grains such as rice dominated, while for others fruits or vegetables dominated the diet. Based on dietitian's coding, average daily caloric intakes ranged from 520 to 1,480 kcal, and energy expenditure ranged from 1.9 to 3.6 kcal/min. Over the 2-week periods, subjects' exposures to food environments ranged from 36 to 267 unique food establishments. Caloric intake was positively correlated with energy expenditure (r=0.11). Exposure to food establishments was inversely correlated with caloric intake (r=-0.17). From our analysis of the EMA data, of the meals associated with "happiness" in EMAs, 70% occurred with friends and family.

IV. BEHAVIORAL INTERVENTION MODEL

Traditional epidemiologic modeling approaches based on coarsely resolved temporal data limit our ability to explore and predict the relationships between behavioral processes, such as diet, physical activity, and mood. Systems science approaches have been proposed for studying health behaviors, and obesity specifically [10]. We begin our model formulation based on the above data we have observed from the Kunming CalFit study.

The correlations between caloric intake and energy expenditure suggest a conceptual framework for modeling an individual's dietary behavior. We assume that dietary intake is associated with energy expenditure from physical activity. This conceptual model can be represented by a set of continuous ODEs or a discrete-time model. Given our interest in obesity intervention, we first assume that at a basic level, weight gain is governed by energy balance: energy expenditure from physical activity (E) is replenished through diet (D), with excess energy intake resulting in weight (W) gain:

$$dW/dt = D(t) - E(t) \tag{1}$$

However, diet at any given moment may be influenced by previous exercise:

$$dD/dt = E(t) \tag{2}$$

More generally, diet may be also influenced by the food environment around an individual (F), as well as social factors (S), such as meeting with friends and family:

$$dD/dt = g[E(t), F(t), S(t)] \tag{3}$$

While dD/dt could be estimated with data using a variety of multivariate approaches (e.g. generalized linear models, tree regression, neural networks), we will comment on the nature of human behaviors that may allow us to transform (3) into variables that may be more amenable to intervention.

Humans are creatures of habit. One of the reasons why behavior change is inherently difficult is because individuals may become accustomed to certain habits, and these habits become routine repeating patterns of behavior. As such, behavioral variables such as E, F, and S may be repeated in time:

$$\begin{aligned} E(t) &= e(i,j,k) \\ F(t) &= f(i,j,k) \qquad (4) \\ S(t) &= s(i,j,k) \end{aligned}$$

where e, f, and s are functions of time: i is hour of day, j is day of week, k is week of the month, etc. The reprojection of E, F, and S to variables i, j, k can be performed using Principal Components Analysis, which results in e, f, and s being linear models. Similar approaches have been used to study travel behavior, and has been called analysis of Eigenbehavior [11]. While e, f, and s could be modeled specifically for an individual with sufficient long-term monitoring data, intervention programs might benefit from inclusion of other tailoring covariates (e.g. age, gender, race/ethnicity, health status) in order to generalize extensive monitoring data collected on a relatively small number of individuals to larger populations.

In our study, we used multivariate linear models to examined the relationship between portion sizes consumed during each meal, and whether it was related to the preceding hour of energy expenditure, mood, and environmental

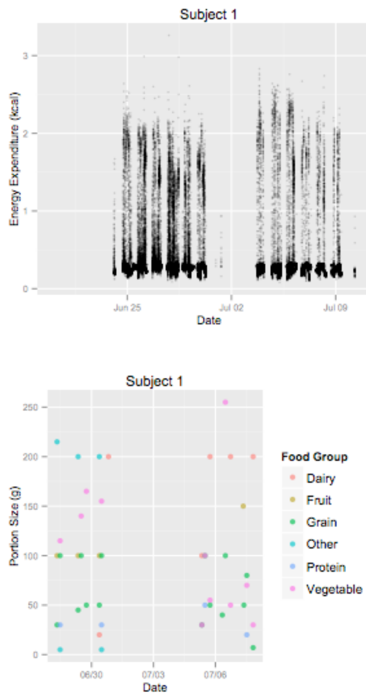

Figure 5. Subject 1's Physical Activity (top) and Dietary Intake (bottom) data.

situation. Hence, our approach explicitly links these different aspects of behavior based on time (i.e., E(t), F(t), S(t)). Our preliminary findings from the multivariate modeling suggests important relationships between some of these factors. First, we found that increased energy expenditure was followed by larger consumption of protein ($p=0.12$), after adjusting for other factors. Also interesting for this student population, we found that less consumption of vegetables was associated with meals at home ($p=0.04$) and at school ($p=0.08$). And, increased consumption of grains occurred when students had less energy expenditure ($p=0.01$), and resulted in students being less tired ($p=0.19$).

V. Discussion and Future Work

Our study illustrates the feasibility of using smartphones to collect an integrated set of behavioral data for individuals that are highly detailed in space and time. While our preliminary analyses are limited by the small number of study subjects, and only two weeks of monitoring data, our findings have led to a larger study involving more than 100 subjects and longer monitoring periods, which is currently in progress. Data from the larger study will help develop more robust parameterization of models that integrate different aspects of behavior. A key feature of the preliminary findings is the temporal relationships between dietary consumption and factors such as energy expenditure as well as mood.

In the future as temporal sequences are better understood for specific individuals, we may be better positioned to use smartphones to routinely monitor and to provide time-based feedback, which could build self-awareness of poor habits that may be reoccurring that may not be immediately obvious to people because they are multifactorial. Feedback could be implemented in the form of suggestions for healthy alternatives to unhealthy behaviors or perhaps incentives that are offered for adoption of healthy behaviors. This feedback could be delivered in a variety of creative ways (e.g. notifications on the phone, automated scheduling of events in the person's calendar, interfacing with social media, or in the form of games). Additionally, technology-assisted feedback could complement human feedback. Health coaches – individuals trained in skills such as motivational interviewing [12], could benefit from automated systems that collect behavioral data from individuals, apply models to identify temporal relationships and patterns in the person's behaviors, and brings these to the attention of the Health Coach for possible discussion with their patients. As we look to the future, many of these approaches will require further evaluation to determine effectiveness.

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