HealthAware: Tackling Obesity with Health Aware Smart Phone Systems

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Abstract—Obesity prevention requires individuals to have healthy eating and physical activity awareness in their daily lives. New technological products have been explored to help monitoring individual health behaviors. Smart phones are ubiquitous hand-held tools with rich embedded sensors and limited computing power. A smart phone is a prospective candidate to integrate physical exercise analysis and food intake monitoring. This paper presents a novel health-aware smart phone system (HealthAware) which utilizes the embedded accelerometer to monitor daily physical activities and the built-in camera to analyze food items. The system presents the user’s physical activity counts at real time to remind how much daily activity is needed to keep healthy. The user takes pictures of food items and the system provides health related information regarding to the food item intakes. The system is composed of an on-device database which holds the user specific data and food item information. HealthAware is a real time practical system to prevent obesity by enhancing individual daily healthy behavior awareness.

I. INTRODUCTION

Obesity has been an epidemic phenomenon in the advanced countries. In the past three decades obesity rates for both adults and children in the U.S. have increased significantly. More than one third of adults and sixteen percent of children are obese. Obesity has posed to be one of the biggest public health challenges to the general population and social welfare. Severe health consequences of obesity include diabetes, stroke, and heart disease. The obesity related health care costs was estimated $117 billion in 2002 in the U.S. alone [1,2]. The continuing increase of overweight and obesity attributable spending attracted increasing research interest to explore practical new technology to prevent obesity.

Obesity prevention requires individuals to foster a life-long healthy food choices and regular physical activities [3,12]. The general case is that individuals with potential obese problem are more likely to ignore their food intake and regular exercises. To promote obese awareness in people’s daily lives is the focus of current approaches to address this issue. One approach propagated by academic research, health clubs, public health programs or even by commercials is to encourage individuals to pursue more physical activity in their daily lives. While it’s easy to believe the importance of regular daily physical activity, there’s lack of practical system to analyze and remind individuals in real time. Developing such systems becomes imminent requirement [5-7]. Another approach propagated by food providers like food item manufacturers and restaurants is to label nutrition information for their products. Unfortunately this kind of information is usually ignored by most of the consumers. Even for the careful consumers the nutrition information is hard to convert to the calories or to be related to possible weight gain.

New technologies have been adapted to help confront the obese challenge. Computers, cell phones, internet services, and game devices become the choices to boost obese prevention awareness. USDA’s MyPyramid [4] developed a tool box to provide handy obesity-prevention resources for adults and youngsters to use. The users register on the web site to create their appropriate meal plan and physical activity schedules. Smart phones are ubiquitous hand-held tools with rich embedded sensors and limited computing power. A smart phone is a prospective candidate to involve in monitoring real-time human health status. Applications utilizing mobile phone functions include [5-11]. PmEB [5] is a menu-driven self-monitoring system which utilizes mobile phone internet access to help users to track their real time calorie balances. Toscos et al. [6] designed a preventative health cell phone application which is named Chick Clique. It uses pedometers and cell phones to motivate teenage girls to exercise. TripleBeat [7] is a mobile phone based system that assists runners in achieving predefined exercise goals via musical feedback. These proposed works exposed the trend to utilize the inexpensive mobile devices to confront the obese problem. How to make such devices accurate in analysis and practical to use remains a challenge.

Motivated by the usage of online nutrition database, the mobile phones as user friendly interface and the pedometer usage to analyze the physical activities, this paper presents a novel design utilizing the smart phone’s rich embedded sensors to tackle the obesity problem. Modern smart phones integrate popular functions such as wireless network interface, GPS, camera, and accelerometer together. The memory capacity and computing power have been increased significantly in the recent years. This paper presents a health aware smart phone system (HealthAware) which develops an obese prevention application utilizing the embedded camera, accelerometer and GPS all-in-one with a single smart phone. It extracts the physical activity data through built-in accelerometer readings. It uses the camera to monitor the food intake. The GPS
information helps efficiently indexing the pictures into the health database. The HealthAware will serve as an individual tool as well as an entertaining social network platform to make people aware of relationship between their health and the food intake and daily physical activity.

To make the HealthAware successful, we must surpass the limitations of a single smart phone resource restrictions. The smart phone has limited storage, restricted wireless communication bandwidth, and limited computing power. An efficient algorithm to analyze the physical activity based on the single built-in accelerometer will be developed. Practical and efficient algorithm to analyze food item pictures is discussed. A database on health information of food items is created to support the on the fly queries. The remaining of the paper is organized as follows: In the next section, we introduce the HealthAware system architecture. In the physical activity analysis algorithm section we present an algorithm that dynamically quantifies the daily physical activities and relate to individual health status. In the food item picture conversion and the database structure section we explore practical methods to extract food calorie information from meta data and the image data. The experimental evaluation section discusses the experiment results of the HealthAware. Finally the conclusion section discusses the current HealthAware design and proposes future work as extension of this paper.

II. HEALTHAWARE SYSTEM ARCHITECTURE

A. The Physical System

The smart phone we use for this pilot prototype design is an HTC Touch Diamond device. It runs Windows Mobile 6.1 Professional system with single processor running at 528MHz. It has 192MB RAM and 4GB of internal storage capacity. The total weight with battery is as light as 110g. It has 2.8-inch LCD touch screen. It has two built-in cameras, one GPS, one static triaxial accelerometer, one microphone, one speaker. It provides GSM, WiFi and BlueTooth network services.

B. The System Design

As figure-1 shows, the HealthAware consists of four components: user interface, on-device database, physical activity analysis system, and food item classification system. The user interface must be simple, easy to use otherwise it will defer its acceptability [3]. The on-device database holds user specific data and general information regarding food items like food names, picture feature data, calories etc. The user specific data includes user physical activity data and food item intake data. The physical activity analysis system works at background to obtain the user’s physical activity by analyzing the accelerometer readings. The food item classification system is responsible to take a food picture, extract meta data from the picture and index into the database.

The user interface includes the a monitoring display screen and an interactive window. The monitoring display screen is shown in Figure 2. It displays daily activities in walking steps and running steps, as well as the steps needed to take for the day. It gives the suggested steps to burn the intake food items. It reports when the user takes the last activity, the user’s current location and any alarming message generated by the system.

The user interactive window is designed as a single level menu but with dynamic user friendly prompts. The main menu includes the following buttons: 1) Initial Training; 2) Take Picture; 3) Health Balance; 4) Food Picture Conversion. Upon starting the Initial Training, the user is prompted by recorded voice messages to stand still, walk and run to train the HealthAware system. During this training the HealthAware detects and sets the user specific parameters for future use of counting the walking and running steps. Upon pressing the Take Picture button, the food item picture is taken and saved to the on-device database. Health Balance button reports the calories difference in steps between the calories intake and spending. The Food Picture Conversion function is designed under the consideration that it’s possible that there’s no match with the food picture in the database. In this case, the HealthAware prompts the user an option to input the food item.
Current research approach to classify daily activities with accelerometry includes fixed-threshold methods, pattern based approach, fuzzy logic, neural networks, binary tree methods, and hidden Markov model approach. Most of them have been explored on an off-line basis. Our goal is to develop a practical real time efficient algorithm to quantify the daily activities. This algorithm has to accommodate the limited resource of a smart phone with an acceptable accuracy of activity and energy expenditure information. This will serve as a learning platform to further enhance the educational and entertaining perspectives of the HealthAware.

The HealthAware database maintains default food item information as well as the user input information. We consider a few design approaches to implement the database. One approach is to develop a centralized shared database on a desktop which serves as the service center. Under this design, the user data are transferred to the centralized database in real time or at a deterred convenient time. The advantage is that the data could be analyzed efficiently with the more powerful computing capacity of the central server and the users could conveniently share data with each other. The disadvantage is that the smart phone itself will not fulfill the duty of the HealthAware system. Another approach is to design the smart phone to hold the stand-alone database. All data analysis is processed locally and the data is saved locally. The advantage is that each smart phone alone serves the HealthAware functions. The disadvantage is that the database is limited and users collaborative communication is complicated. In this pilot development we will pursue the stand-alone design approach. Our main concern is to explore practical algorithms to implement HealthAware on a single smart phone. In our future development we will explore the hybrid implementation which has a central database with individual smart phones owning their own on-device operative databases.

The third component of HealthAware is the physical activity collection system. It utilizes the embedded accelerometer to analyze the physical activity of the smart phone holder. The system works at background and detects smart phone holder’s movements which contribute to energy expenditure. There have been use of the accelerometer to classify human movements[13-15]. In the HealthAware system we use the accelerometer to count the walking and running movements of the smart phone users. The time, location, and quantified movements information will be saved in the database to be inquired by other functional components. Ideally, the quantified movements data are to be eventually converted into calories spending information. [16] studied the evaluation of calorie expenditures of physical activities. It cautioned that evaluation of calorie expenditure using a triaxial accelerometer are only approximate in people with various health situation. Other methods proposed are either inaccurate or inapplicable to our single smart phone system. So we will relate the activities and food items by converting them approximately into walking or running steps.

The last component is the food picture conversion system. This is a component which enhances entertaining and promotes usability of HealthAware. It serves the calories intake monitoring function. Previous work [5] has been done to use the cell phone to monitor the real time calories balance. It asks the users manually input the food information which impedes the acceptability of the product. In our pilot prototype implementation, the HealthAware’s food picture conversion system uses a preloaded food item system and the user input food item name to get the calorie information. Eventually the system will convert the picture into the corresponding energy expenditure information once an efficient visual recognition algorithm is developed.

III. PHYSICAL ACTIVITY ANALYSIS

This section presents a practical algorithm which will be capable of quantifying the physical activities and estimate the equivalent energy expenditures. Since the main purpose of HealthAware is to help promote the awareness of exercise to health, we will mainly classify moderate and intensive movements from walking movements and running movements. We focus on the number of actions, intensity level and duration of the physical activities in walking steps and running steps.

Walking and running activities bear the similar action patterns. A person’s walking gait is a cycle of step forward, step down and hold. During the step forward stage, the user spend energy to gain acceleration and momentum upward and forward, which requires the most of the energy expenditure. At the step down stage, the momentum of the body continues to increase because of the gravity. When the forward foot touches the ground, the ground holds the body and counters the vertical momentum and part of the forward momentum of the body. After that, another gait cycle starts. A running activity bears the similar action pattern but with a stronger intensity. We present the following figure to demonstrate these activity patterns.
We apply a noise filter to the accelerometer readings. Instead, we examine the reading to see if it's changed. The valid total accelerometer reading then becomes:

\[ AV_{t} = \sqrt{AV_{x}^2 + AV_{y}^2 + AV_{z}^2} \]  

(1)

The low pass filter is applied to filter out the high frequency values within one single activity cycle so that the false positive count will be avoided. It’s implemented in real time as a dynamic sliding window by examining the peak value intervals. Any vibration signal within the activity cycle will be ignored. The activity cycle is specific to different users. Hence a dynamic training mechanism is developed to ensure the system to be user specific. Similarly the high pass filter is applied to filter out the non-human movements such as vehicle movements or elevator movements. The application of the dynamic sliding window will be utilized to eliminate the non-human movement signals.

To cope with the varying parameters of the base filter, the low pass filter, and high pass filter, we developed a neural network mechanism to dynamically detect the real time values. When the system first starts up, the user is prompted to train the system to get the initial parameters. At first, the user is prompted by recorded audio messages to stand still to get the base acceleration reading. Then the user is prompted to walk for 20 steps to set the walking threshold values. At last, the user is asked to run for 20 steps to set the running credential parameters. Later on, the system is periodically test the base filter value to adjust the situation when the smart phone is repositioned during the day.

The physical activities are categorized into walking steps and running steps during the day. According to the health information provided by Mayo Clinic [17], a healthy physical activity count is suggested to be 10,000 walking steps daily or 3,000 running steps daily. We use these numbers as a standard to compare with the accumulated count. The screen message on the smart phone will inform the user how much activity has been done and how much will be needed to maintain the healthy standard.

### IV. Food Item Picture Conversion and the Database Structure

Food item categorization and classification through visual images present a challenge to the current theory and technology on visual object classification. Alternatively, we consider multilevel meta data indexing on fast food restaurants food items in this paper. We use GPS data of the smart phone to be the first index into the food item database. By using this index, a picture is categorized into some specific restaurant which only a class of pictures will be considered to compare with. To further narrow down the food items we use the time of the picture taken as the secondary index into the database. This will leave smaller category of possible candidate pictures to compare with. Further, we use the food name of the user input as the identification vector index to the database. To notice that in the future research we will develop applicable algorithms to directly extract picture feature vectors to replace the food item names. That will further free the user inputs. This three level indexing mechanism as demonstrated in figure 5 is essential on the stand-alone approach of the HealthAware database design in which the food item identification consumes significant amount of computing resources.
Figure 5 displays the user interface to take a food item picture. The user has options to set a directory, file name and title for the food item picture. If there’s no input the default directory and file name will be used. As stated in the previous paragraph, for now we will use the picture name as the last index to identify the food item. Hence the picture name is required to query the food item calorie database.

The on-device database composes of preloaded food item information and user specific data. They are maintained in relational tables defining the following relationships.

- GPS data $\rightarrow$ Restaurant code
- Restaurant code $\leftrightarrow$ Restaurant name
- Food item name $\rightarrow$ Food item code
- Food item picture identification vector $\rightarrow$ Food item code
- Eating time $\rightarrow$ meal type (breakfast, lunch, or dinner)
- Restaurant code, meal type, food item code $\rightarrow$ Calorie information

In the current implementation, the user input name is used instead of the food item picture identification vector. After the user inputs the name of the food item picture, the system obtains the GPS data and current time and save them as meta data along with the picture. The module retrieves calorie information and adds it up for the monitoring module to display. This alleviates the frequent calculation request if we would design it to be calculated at request time. For the infrequent health-balance request, it will query the database to gather the data in real time. The calories are evaluated in the units of walking steps. The exact calories burned during exercise depend on the individual’s weight and exercise intensity. On average every 20 steps will burn one calorie [18]. We use this conversion formula in the current prototype.

V. EXPERIMENTAL EVALUATION

In this section we will test our algorithms to quantify the physical activities and identify the food items. We develop the software using C++ programming language with Windows Mobile 6 SDK on a desktop machine. We deploy the target code to the HTC Touch Screen smart phone. The application is tested on the smart phone alone. The essential demands we put emphasis on are accuracy, flexibility and efficiency. The system should be able to quantify the daily walking and running activities and food intake in certain accuracy. It should be adaptable to people with various activity intensities and it should work for common wearing positions of the smart phone. The on-device processing should be efficient enough to catch up with the activities and promptly provide analyzed information.

A. Experiments with the activity quantification algorithm

To demonstrate that the base accelerometer readings vary when the smart phone is positioned differently, we collect the data with the smart phone face-up, face-down, stand-up, upside-down, left side up and left side down. The base values are 8.8, 10.7, 9.9, 9.7, 9.7, 10.1 respectively. Therefore the traditional method of subtracting the standard 9.8 m/s$^2$ from accelerometer readings doesn’t work. We have to dynamically find out the base value when the smart phone is mounted. This is done through the initial training and occasional adjustment on the fly. At first the user is prompted to mount the phone, keep still, walk and run to train the system. Later on, when the system detects a stagnant period it will recalculate the base accelerometer value to accommodate possible reposition of the smart phone.

Various intensities of people’s daily activities require that the threshold values for walking and running be different. The system acquires such values during initial training. The initial training asks to stand still for 10 seconds, to walk for 20 steps, to run for 20 steps. During testing with various people, we found that these settings are acceptable although it’s commented that shorter time and fewer steps would be preferred. We tested our system by placing the smart phone on different places with people of various activity intensities. We tested both on treadmills and on street roads. The results all proved that the algorithm is successful to differentiate walking from running and to count the steps respectively with accepted accuracy.
Scenario 1: People with stronger activity.

<table>
<thead>
<tr>
<th>Phone Position</th>
<th>Walking Count</th>
<th>False Count</th>
<th>Running Count</th>
<th>False Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hold still in front of chest</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>On waist belt at the side</td>
<td>100</td>
<td>0</td>
<td>97</td>
<td>0</td>
</tr>
<tr>
<td>On waist belt at the hip</td>
<td>56</td>
<td>13</td>
<td>93</td>
<td>0</td>
</tr>
<tr>
<td>In upper body pocket</td>
<td>100</td>
<td>0</td>
<td>98</td>
<td>0</td>
</tr>
</tbody>
</table>

Scenario 2: People with weaker activity.

<table>
<thead>
<tr>
<th>Phone Position</th>
<th>Walking Count</th>
<th>False Count</th>
<th>Running Count</th>
<th>False Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hold still in front of chest</td>
<td>100</td>
<td>0</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>On waist belt at the side</td>
<td>98</td>
<td>0</td>
<td>98</td>
<td>0</td>
</tr>
<tr>
<td>On waist belt at the hip</td>
<td>95</td>
<td>0</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>In upper body pocket</td>
<td>105</td>
<td>0</td>
<td>97</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 1: The two activity scenarios: strong and weak activities

In Table 1, we presented test results from two activity scenarios. In both scenarios we asked the user to walk for 100 steps then run for 100 steps. The first one is a set of results from those with strong intensities which resemble healthy, young or middle aged men and women. The second set resembles weak or old people’s activities. When the smart phone is held still against the chest the walking counts and running counts are 100 percent correct in both scenarios. When the smart phone is set in other places, some miscounts exist. This is explained by the fact that our algorithm differentiates and quantifies walking and running by evaluating the whole body movements. When the smart phone is attached to the belts or in pocket, some extent of the movements from the smart phone itself caused incorrect analysis. To be noticed is that the hip position shows the most deviation and some running steps are counted to the walking steps. The practical waist side position showed the best results.

During the experiments, all counts were simultaneously reported on the screen as the activities took place without any delay. This proves that our algorithm works at real time.

**B. Experiments with the picture taking**

The picture taking application enhances entertainment and attraction to the HealthAware users. After the user clicks the Take a Picture button, the screen in figure 6 displays. The user inputs the name of the file which will be used as the name of the food item. As an option the user could input the calories in the title section. After the user click Start button, the screen shows the normal picture taken window and the user can go ahead use the physical button located in the lower middle part to take the picture. This process is acceptable to the users but it’s commented that no user type-in will be preferred.

**VI. Conclusion**

In this paper we presented HealthAware, a novel design to utilize the built-in accelerometer and camera with a smart phone. It’s capable of monitoring individual’s daily physical activity and food intake with limited user interference. It integrates all functions within a single smart phone. By adapting the neural network algorithm the system is successful in differentiating and quantifying walking and running activities in real time with various moving intensities. It uses the embedded camera as the food intake information channel which presents a promising research topic. In the future research as extension of this pilot study, we will develop a more thorough real time quantifying algorithm to evaluate more categorized daily activities. We will explore an efficient visual classification algorithm to free the user input and make this system more attractive. We believe the HealthAware system will be eventually to help enhance the health awareness and tackle the obesity problem.

**REFERENCES**


