Abstract: California like the entire nation is aging. There are 4.3 million Californians 65 and older accounting for about 11% of the total state population. We also find that 58% of older adults have high blood pressure; about 21% have been told that they have diabetes. California in particular has the highest incidence of new diabetes cases and nearly 4 million people (diagnosed and undiagnosed) are estimated to be suffering from the disease. Diabetes is a chronic disease, which if unchecked leads to acute and long-term complications and ultimately death. Our older adult population often lacks the cognitive resources to deal with the daily self-management regimens. Many unpaid family members are caring for them today but this is unsustainable. In this paper, we discuss the design and implementation of a wireless sensor network system within the home environment that captures activity of daily living. We mine the data and provide feedback via SMS/text (daily) and tailored newsletter (weekly). We introduce a novel idea called “persuasive sensing” and report results from two home implementations that are showing exciting promise. Moreover we show that with the help of an Artificial Neural Network, we can predict blood-glucose levels for the next day from accumulated data with an accuracy of 94%. The predictive model presented here is a break-through in at-home sensing research.

1. Introduction

Diabetes mellitus is the most common and serious chronic disease in the United States. There are nearly 26 million Americans with diabetes, 30% of which are aged 65 and older [1]. California in particular has the highest incidence of new diabetes cases and nearly 4 million people (diagnosed and undiagnosed) are estimated to be suffering from the disease [2]. According to the 2010 census, there were 4.3 million Californians 65 and older (referred to as older adults from now on) accounting for about 11% of the total state population. More specifically, of the 4.3 million, about 86% are age 65-84 and about 14% are age 85 and older [2, 3]. Exploring further we find that 58% of older adults have high blood pressure, about 21% have been told that they have diabetes. 37% of older adult Californians are classified as overweight and about 22% are classified as obese [2]. The most worrisome statistic is that the number of Californians age 65 and older is projected to increase by 100% from 2010 to 2030 (7.75 million as the Baby Boomer generation turns 65 years old) [4].

The global population is getting older [1]. When we consider the state of California (our residence), we see an impending crisis that is emerging. Diabetes is a chronic disease characterized by a sustained elevated blood glucose level, caused by a reduction in the action of insulin secretion where related metabolic disturbances generate severe, acute and long-term complications that are responsible for premature death and disability [5]. The World Health Organization projects that diabetes deaths will increase by more than 50% in the next ten years without urgent action. Most notably, diabetes deaths are projected to increase by over 80% in low-middle income countries between 2006 and 2015 [6]. The costs of caring for this disease are astronomical and are estimated to exceed more than $24 billion in California and $174 billion nationally [1, 2, 4].

These older adults are receiving long-term care services which are being provided in a variety of settings including one’s home (home care), in the community (e.g., adult day care), in residential settings (e.g., assisted living or board and care homes), or in institutional settings (e.g., intermediate care facilities or nursing homes). In 2007, 4 million Californians served as unpaid caregivers to an adult or child. The majority of unpaid caregivers in California (85%) are family members and almost half of unpaid caregivers are caring for a parent. In 2010, approximately 42% of Californians 65 and older are living alone.

This situation is unsustainable. While diabetes is a dangerous disease, it can be managed if the patient can adhere to recommended ADA self-management guidelines [5]. Regularly measuring blood-sugar
levels, staying physically active, watching diet and calorie intake, and not forgetting to take medications and insulin can help to manage the disease. Yet our older adult population lacks the cognitive resources and problem-solving skills to deal with the daily regimens. While unpaid family members are caring for them, we see tremendous potential of healthcare information technology to assist. In this paper, we discuss the design and implementation of a wireless sensor network system within the home environment that captures activity of daily living. We mine the data and provide feedback via SMS/text (daily) and tailored newsletter (weekly). We introduce a novel idea called “persuasive sensing” and report results from two home implementations that are showing exciting promise. Moreover we show that with the help of an Artificial Neural Network, we can predict blood-glucose levels for the next day from accumulated data with an accuracy of 94%. The predictive model presented here is a breakthrough in at-home sensing research.

2. Background

Mobile phones are an ideal platform for sending feedback to diabetes patients because they are ubiquitous, low-cost, reliable, real-time, and versatile; and unlike most technologies, actually enjoy greater usage amongst racial and ethnic minorities. Mobile phones can be a self-management tool that can help individuals to remember various health-related activities and record them, and also help others in their personal wellness ecosystem to review ongoing health patterns and respond quickly to changes in health status [7, 8].

In this paper we describe the design, implementation and evaluation of such a mobile and wireless sensor system. In particular we leverage our groundbreaking work in “persuasive technologies”, which are applications and devices intentionally designed to change user behavior [9-12]. In our implementation, older adult patients with diabetes receive customized text messages based on their sensor data to motivate them towards a healthier lifestyle. They also receive a customized health newsletter (weekly) that is aimed to inform and educate them on their various daily activities.

2.1 Related Work

Using wireless sensor networks within the home can help to remotely monitor activity of daily living (ADL) [13, 14]. Such data if mined properly can identify health patterns which can then be used to send effective reminders and feedback [15, 16]. In [7], a smartphone app to self-manage diabetes has been proposed. In [17], simple SMS reminders have been shown to be promising in increasing compliance. Medical devices, information technology and mobile communications have started to converge; this has the potential to revolutionize healthcare in the home [13, 18]. In [19], various consumer level electronics along with wireless networking capability have been utilized to help monitor various diseases. At-home healthcare can help address the social and financial burdens of an aging population. At the same time the technology can support the network of care-givers such as family members, neighbors, and friends with new and innovative ways to monitor the wellbeing of older people, increase the levels of communication with the older person and to enable rapid response to emergency situations. Our technology is aimed at lowering care-giver burden while enhancing the patient’s quality-of-life.

3. Persuasive Sensing System Architecture

Any at-home healthcare solution must detect and respond to the activities and/or characteristics of the older person. A network of sensors (worn, carried, or environmental) is an ideal technology platform for detecting and responding to health-relevant parameters such as movement, sleep, weight, physiological data and social activity [13]. In designing our system, the following key principles were kept in mind throughout the process:

- This is a healthcare problem, not a technology problem. At the center is the patient, not the technology. That also means as the experiment progresses, we must adapt based on patient’s feedback.
- The simpler the technology, the better. Patient must comprehend what is being sent as feedback.
- Wireless Sensor Networks (WSNs) for healthcare are mission-critical; reliability is of paramount importance.
- The daily feedback persuasive messages must be kept fresh and not boring so that patient is eager to receive them and learn how to change his/her behavior.
- It has to work in the home, not just in the lab.

A WSN device is a packaged data collecting or actuating component, which includes a sensor and/or actuator, a radio stack, an enclosure, an embedded processor, and a power delivery mechanism [13]. The sensor interacts with the environment and sends an appropriate signal (analog or digital) to the
embedded processor (also called microcontroller unit). We used Iris Mote technology developed by Intel and UC Berkeley labs. The mote hardware platform consists of a microprocessor and radio chip (MPR: Mote Processor Radio Board). Sensors connect directly to the mote processor radio boards via various interfaces. This combination gives the mote the ability to sense, compute and communicate. The mote enables raw data collected by the sensors to be analyzed in various ways before sending it to an aggregator (in our case a laptop) that we placed within the home. The aggregator then uploads daily activity data to the cloud through secured channels via the Internet. The following different types of sensors were implemented in this project:

**Ambient Sensors**: A simple on/off switch that detects open/close of garage door (through which subjects leaves homes), detects the back porch door for outdoor access. An infrared analog sensor was used to detect presence in the bedroom. A pressure pad sensor (from Colonial Medical) was placed in the couch in the living room in front of TV. Simple on/off switches were used to detect opening and closing of medication cabinet and the cabinet containing insulin. A photo sensor was connected to the TV to detect television viewing.

**Device-level sensors**: A blood glucose monitor device was chosen that can connect easily to the laptop via USB and can upload blood glucose values daily. A wireless weight machine (from Tanita Corporation) that sends value via Bluetooth was placed in the family room.

**Body-wearable sensor**: A commercial body-wearable sensor from BodyMedia Inc. which is an armband was given to the patient to wear 24 hours. This multi-sensor senses number of steps walked, quality of sleep, and many other physiological parameters such as skin temperature. Data is uploaded to the cloud by connecting it to USB port for less than five minutes daily.

<table>
<thead>
<tr>
<th>Case</th>
<th>Steps &gt;= 8000</th>
<th>Steps &lt; 8000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mon</td>
<td>Great Job! Keep up the good work.</td>
<td>Don’t give up on physical activity. Try walking a mile each day.</td>
</tr>
<tr>
<td>Tue</td>
<td>You have exceeded your goal. Congratulations.</td>
<td>Don’t give up physical activity. Have you taken the stairs?</td>
</tr>
<tr>
<td>Wed</td>
<td>You are doing very well. Keep it up!</td>
<td>Have you reached your goal of 8000 steps?</td>
</tr>
<tr>
<td>Thu</td>
<td>You are a super hero. You have exceeded your goal.</td>
<td>You fell short of your goal. Don’t worry. Try to walk a mile after dinner.</td>
</tr>
<tr>
<td>Fri</td>
<td>You have exceeded your goal. Super job!</td>
<td>Never say never. You can do it.</td>
</tr>
<tr>
<td>Sat</td>
<td>Steps graph for past 5 days</td>
<td>Try some brisk when you are in the parking lot.</td>
</tr>
<tr>
<td>Sun</td>
<td>Great Job. Enjoy the Sunday with friends and family.</td>
<td>It is a beautiful day. Go out and do brisk walking for 30 mins.</td>
</tr>
</tbody>
</table>

Table 1: Messaging algorithm for physical activity

The subject was shown how to log into BodyMedia website where he/she could input diet/nutrition information. Our system would then fetch daily diet data and we could then compute total calories consumed. We also provided the patient with bottled water and asked them to only drink that during the course of the experiment. This was a simple way for us to monitor water intake. The overall sensor placement within the home is shown in Fig.1.

4. Intervention Design and Persuasive Messaging Algorithms

Patients with type 2 diabetes can manage their chronic conditions by following certain recommended strategies. Prevention strategies for Type 2 diabetes include:

- Lose weight and keep Body Mass Index (BMI) under control
- 30 minutes or more of exercise or physical activity (brisk walking every day is fine)
- Develop a low calorie and low fat diet. Nutrition guidelines include recommendations for diet rich in whole grains, fruits and vegetables.
Take necessary medications (including insulin) and measure their blood sugar level regularly. Most elderly patients cannot adhere to these regimens due to lower cognitive abilities and lack of resources to maintain the lifestyle. Hence with technology, it is now possible to help these patients.

Our intervention has multiple components.

- System sends daily Short Message Service (SMS) on cell phone. They are persuasive messages targeting behavior change.
- A tailored newsletter that summarizes healthy living parameters is presented to subject once a week and is jointly read by family member or one of our research team members.

Note our intervention (through the prototype persuasive sensing system) is aimed to engage patients in diabetes self-management through interactive SMS and newsletter approaches. It was important to ensure that daily text messages sent to the subject were fresh and relevant. Each day the subjects received up to 3 text messages that were delivered to them over an LG smart phone (subject 1) and an iPhone (subject 2). Prior research has shown the efficacy of telephone reminders [17] and technological cues. However our system sends feedback on actual subject’s daily behavior, which is much more targeted and context relevant. Above we show an example of how messages were varied for physical activity (Table 1). The physical activity is measured by the number of steps obtained from the Bodymedia sensor. Similar daily text messages were sent for calorie intake, blood-glucose measurement values and sedentary activity. The customized newsletter is a PDF file that is about 4-5 pages and carefully summarizes the details of the subject’s weekly performance. The newsletter was read together by the subject and one of our team members.

5. Subject Recruitment and Research Design

We obtained approval from our university Institutional Review Board (IRB). With IRB approval, we distributed announcements to recruit subjects via hospitals, diabetes clinics and through personal contacts. The basic eligibility criteria that we included in our recruitment efforts were:

- Subject must have Type 2 diabetes
- Age can be between 45-85
- Gender and race – no preference
- Have familiarity with cell phone and texting

Have a broadband internet connection at home

We received some prospective candidates who expressed interest. From the pool we selected two subjects. The first subject was an 82 year old white male who is retired and lives in the Vista community near San Diego. He has type 2 diabetes, and also a few other health problems. He agreed to the consent form and we started our project implementation. The second subject was a 60 year old white female who lives in San Diego. She also has type-2 diabetes, hypertension and is obese. She had elevated BG levels and was considered a high-risk subject.

We specifically designed a pre-post type of intervention (see Fig. 2). The two homes were sequentially implemented. The first implementation was at the male subject’s home which started on October 18, 2011 and ended on November 25, 2011. The second home implementation was the female subject which started on January 2 and ended on March 1. We encountered certain unnecessary delays with our second subject due to travel. All sensors and other equipment’s were removed from subjects home after the intervention. We thanked the subjects and gave them a token honorarium for their participation.

<table>
<thead>
<tr>
<th>Pre-Study</th>
<th>Post-Study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting Survey</td>
<td>Set Up</td>
</tr>
<tr>
<td>1 week</td>
<td>1 weeks</td>
</tr>
</tbody>
</table>

Testing Baseline Intervention

6. Results

The trend lines for BG-levels (Fig. 3A) for both the subjects show a gradual decline. This shows positive improvement in maintaining BG levels. Both the subjects were asked to get their HbA1c (considered a 90-day average of blood sugar) before and after the intervention. For subject #1, HbA1c dropped from 12.8% to 6.6% which is a significant improvement (50% decrease). For subject #2, HbA1c went down from 8.9% to 8.5% which is a positive result but smaller improvement. It’s easy to see that subject #2 had greater daily fluctuation of her BG-levels. The
weight (Fig. 3B) and idle-time (Fig. 3C) trends also show a gradual decline. From Fig. 3D, it shows that the trend in number of steps walked (which reflects physical activity) is increasing. Our daily text messages and newsletter helped to alter their behavior.

7. Predictive models using Artificial Neural Networks

Generally, the field of predictive analytics entails the use of a multitude of techniques from statistics, artificial intelligence, and data mining based on previous collected sensor data or learned knowledge to make decisions about the present state or future. The field of predictive analytics can be divided into three general categories of model types: predictive models, which make near-term projections based on previous data; descriptive models, which classify data based on commonality of characteristics in the data; and decision models, which are used to interpret data and take actions based on the interpretation, according to a predefined set of rules. In this section we explain and demonstrate an approach for health behavior profiling by applying machine learning techniques to human behavior data captured by sensors as described before. Some of the key challenges in developing such profiles are:

i. The sensor data may have some inaccuracy.

ii. The daily behavior pattern of a human may differ from day to day.

iii. There may be some deviation in the daily routine activities due to unexpected scenarios such as but not limited to guest’s arrival at home, and some urgency in family.
We need to develop an approach that addresses these situations but still be able to model human behavior, which can be used for disease profiling. Fundamentally we have relied on Replicator Neural Network (RNN) [20] to model human behavior. Traditionally RNN has been used for anomaly and outlier detection. For each subject, we identified the first 14 days (2 weeks) of data as the **training data** and the rest of the data as the **testing data**. Thus for subject 1 we had 7 days of testing data and for subject 2 we had 16 days of testing data. Each data point in both the training and testing data set had 11 fields as described before.

One of the key characteristics of a RNN is the input and outputs are same. In our scenario, we have used daily human behavior data (such as number of steps, hours of sleep, time in couch, time in watching TV, number of times went outside) as both the input and output. The RNN is trained based on the same input and output. During testing, the Mean Square Error (MSE) between the input and output is taken as the indication of whether the test input data follows the pattern derived from the training input data.

One of the challenge in feeding the data of daily behavior into RNN is the data may have some anomalies due to reasons not related to our research and which are out of our control (such as visitor in subject’s home, or long absence from home due to social visit or due to issues related to sensors). The first step in building the profile data is to identify these data items. For this we applied K-mean clustering technique on the daily behavioral data of the subject. The data points related to the largest cluster in the K-mean output is taken as the routine daily behavior of the subjects. This daily behavior data is then fed into RNN as both input and output to train the RNN. Figs. 4 and 5 depict the process. In this paper, we describe our experience of applying the RNN modeling to two subject’s data which were collected from sensors deployed within the home.

Figure 4: Building RNN model for disease profile
We collected the daily behavior data of two subjects (marked as subject 1 and subject 2) over the course of 21 days and 30 days respectively. The data included – (i) weight (ii) blood glucose (iii) number of steps taken (iv) quality of sleep (v) total minutes lied down (vi) total sleep time (vii) Total calorie in-take (viii) bed room time (ix) couch time (x) TV time and (xi) total number of in and out of the house. These data items were computed on a daily basis from the raw sensor data received. Thus the data had 11 columns, one for each data item. For subject 1, we had 21 rows and for subject 2, we had 30 rows (one row per day per subject).

Figure 5: Using RNN model for disease identification
For subject 1, we first applied K-clustering algorithm on these 21 data points. The clustering resulted in only one cluster, indicating that there were no outlier data points. Next, we randomly divided the 21 data points into two groups – training data set and testing data set. The training data set is then fed into the RNN with 11 input variables, 11 output variables and 3 hidden layers each with 8 neurons. Once the RNN model has been built up, we fed the second group, i.e. the testing data set into the model. The average MSE of the testing data for the RNN came out to be just 6.21%. We applied the same approach to second subject’s data with the similar RNN structure, and got a testing error of 3.52%.

This indicates the Subject 1’s behavior can be predicted with an accuracy of 93.79% and Subject 2’s behavior can be predicted with an accuracy of 96.48%. This clearly demonstrates that Subject 2’s behavior can be better predicted than Subject 1’s behavior. The exact reasons for this difference in results need to be investigated. However, we anticipate that the difference could be due to the demographic differences between the two subjects and the nature of daily behavior. For example, Subject 1 was less adamant to change than Subject 2 based on persuasive messages sent.

Overall, the above experiment demonstrates that the RNN served the purpose of profiling the subject based on daily sensor data. Once the model has been built for a subject, the model can be used on daily
basis to identify any major deviation from the profiled model and thus possible health condition that needs attention.

7.1 Predicting Blood Sugar Levels

In this section, we demonstrate how the daily behavior data can be used to build an ANN (Artificial Neural Network) based model for predicting blood glucose level. It is a known medical knowledge that calorie intake and physical activity directly impacts the blood glucose level [21]. However, based on various daily activities, it becomes difficult for a subject to know whether the daily activity and the calorie in-take have been appropriate to reach the target blood sugar level. In this section, we demonstrate an ANN based model that can be used by subject to predict the daily blood sugar level based on behavioral data captured by sensors. We propose two models for this purpose.

For the first model for subject 1, we have 20 data points; note that we don’t have the blood glucose level for 22nd day of the experiment. So we can’t use the behavioral data for 21st day. We prepare 20 data points, where the input is the behavioral and physiological data on day D and the output is the morning blood glucose level on day D+1. We randomly divide the data into two sets – training and testing data set. First we train the model with the training data set. Next, we run the testing data set through the model to measure the testing error. We got an error of 7.5%, i.e. the model is able to predict the next day’s blood glucose level with an average accuracy of 92.5%. We applied the exact same approach for blood glucose level prediction for Subject 2, and got an error of 6.6%, i.e. accuracy of 93.6%.

For the second model, we added the blood sugar level of day D in the input layer. In this model, we predict the morning blood glucose level of day D+1 based on behavioral and physiological data in day D and the morning blood glucose level in day D. Other than addition of the day D morning blood glucose level in the input layer, the neural network structure remains same as in Figure 7. Similar to the previous scenario, here also we divide our data randomly into two sets training and testing. First we train the model and then we test it using the test data. We got a test error of only 4.1% for subject 1 and 6.1% for subject 2, i.e. an accuracy of 95.9% and 93.9% for subject 1 and subject 2 respectively.

Thus, if the blood glucose level is available in a day, based on behavioral data we can predict the expected blood glucose level in the next day morning with an accuracy of 93.9 – 95.9%. If the blood glucose level is not at all available, then we can predict the blood glucose level of the subject with an accuracy of 92.5 – 93.6%. This is a high accuracy of prediction and has major implications for medical decision making research.

Table 2 shows the summary of our experimental results for the various RNN and ANN based predictive models for both subject 1 and subject 2. Considering the complexity of health scenario, we believe these are good acceptable results.
Modeling

| Blood Glucose (BG) Level prediction for day (D+1) from behavioral data in Day D using ANN | 7.5% | 6.6% |
| Blood Glucose (BG) Level prediction for day (D+1) from BG level of Day D and behavioral data in Day D using ANN | 4.1% | 6.1% |

| Table 2: Summary of Results |

8. Conclusions

We designed and build an in-home activity monitoring system using ambient sensors and body-wearable sensors. Using a pre-post experiment method, the subject(s) received daily text messages based on his/her behavior the previous day. These persuasive messages used strategies such as motivate, praise, guilt or reward to encourage positive behavior change. The subject also received a tailored health newsletter at the end of each week that summarized various physiological and biological parameters. Subject 1 showed tremendous improvement in HbA1c levels which dropped from 12.9% to 6.6% when measured after experiment. Subject 2’s HbA1c went down from 8.9% to 8.5%.

We conducted a post-experiment exit survey in which self-efficacy was assessed using an adapted version of Sarkar et al., diabetes self-efficacy (DSE) scale [30]. The DSE scale is a reliable, validated 4-item instrument that assesses patients’ perceived competence in diabetes self-management. Survey result in Table 3 shows that subjects’ ability to manage diabetes is improving. It also indicates that their quality of life is improving as well.

During the implementation, we faced the following challenges:

- The Iris mote sensor system wasn’t functioning sometimes and had reliability problems. A member of the team had to fix the errors several times before it became stable.
- The BodyMedia armband needs to be tight around the skin. However as our male subject was elderly, it would not connect properly sometimes. Also at times it would give some skin rashes to the subject. A solution was to place the Body Media on his leg, and under his sock, which anchors the device against his leg, delivers a better measurement than placing the device on his arm.
- The base station being a Windows XP machine rebooted itself probably due to a security update and that killed many of the processes that we were using. A manual intervention was required in-between deployment to bring everything back to normal state. Sometimes the subject’s home Wi-Fi would mal-function which would affect our ability to collect data.

In future, one needs to design simple aggregation box which would perhaps run Android operating system and have several USB and wireless interfaces (Wi-Fi, Bluetooth, and ZigBee) that would make device interoperability seamless.

The second subject did not seem to respond well to dietary messages. We later found out that her daughter stays close to her in an adjacent apartment and has unfortunately negative influence on her eating habits. This presents an opportunity that we will explore in future.

The RNN model that we have designed shows that it is possible to profile a subject and his/her disease. The RNN testing showed that it is possible to accurately predict relevant medical parameters with 93.9 – 95.9% accuracy. The ability to predict blood-glucose levels 24 hour in advance can be very beneficial. The patient can be notified, family members can be alerted and even the patient’s physician can be notified that adverse health conditions may be impending. Urgent care can then be provisioned.

Our persuasive-sensing system along with RNN modeling of a diabetic patient is a significant contribution towards achieving healthy lifestyles for older patients who are suffering from this deadly disease. Such systems relieves care-giver burden and helps patients to better self-manage their chronic condition. Our present work is a good case study to understand how such technologies work. Our next step would be to scale up to 100 homes and conduct a detailed Random Control Trial experiment.

A significant benefit of such remote monitoring systems is that it relieves care giver burden who are already overwhelmed with case load. We anticipate that such monitoring would become commonplace in
near future and provide aging population to conveniently stay at home and get treatment.

Subject 1 (82 year old male)  Subject 2 (60 year old female)

<table>
<thead>
<tr>
<th>Pre-Persuasive sensing care</th>
<th>Post Persuasive sensing care</th>
<th>Pre-Persuasive sensing care</th>
<th>Post Persuasive sensing care</th>
</tr>
</thead>
<tbody>
<tr>
<td>I feel confident in my ability to manage my diabetes</td>
<td>agree</td>
<td>agree</td>
<td>agree</td>
</tr>
<tr>
<td>I feel capable of handling my diabetes</td>
<td>agree</td>
<td>agree</td>
<td>agree</td>
</tr>
<tr>
<td>I am able to do my own routine diabetes care.</td>
<td>agree</td>
<td>Strongly agree</td>
<td>agree</td>
</tr>
<tr>
<td>I am able to meet the challenge of controlling my diabetes.</td>
<td>neutral</td>
<td>neutral</td>
<td>neutral</td>
</tr>
</tbody>
</table>

Table 3: Diabetes DES exit survey results

Acknowledgement
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9. References


