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Smart Diary –A Guide to Man's Daily Planning 2016

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Abstract—In this paper we present Smart phone app that senses and analyses mobile data to understand, predict, and summarize a man's daily activities, such as his daily routine. These activities are used to represent knowledge, which helps in generating digital personal diaries in an automatic manner. Here we make use of different sensors for the purpose of sensing. Smart Diary is able to make predictions based on a wide range of information sources, like phone's sensor readings, locations, along with interaction history with the users, by integrating such information into a sustainable mining model.. This Android app is specifically developed to handle heterogeneous and noisy data, and it is made to be extensible in which people can define their own logic rules which will express predictions like short-term, mid-term, and long-term events and patterns about their daily routine. The app's evaluation results are based on the platform provided by Android.

Index Terms—*Mobile computing, sensors, Data mining, inference algorithms*

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I. INTRODUCTION

Smart diary is a periodical software which is suited for all men and women- It can be anyone's personal organizer, a health tracker, secretdiary, anutritional tracker, health monitor, contacts organizer, schedule software, tasks manager- all in one a simple to use and integrated package. There are several editions from which you can choose, so that you can be sure that your diary is tailored to your specific needs. A personal diary is the one which records human's experiences, thoughts, and feelings on occasions in the outside world[2]. Some personal diaries like those by Anne Frank, have become popular and widely read books and the basis of plays and films. Besides their value in terms of being a hobby and a literature source, diaries also serve vital roles for scientists in social science. Some researches use diaries to study the relationship between certain activities (e.g., yoga) and health problems (e.g., heart attack) in certain populations Using a smart diary you can plot your exercise or yoga program against your diary of health notes and see how they interrelate[5]. Add information about changes in your diet and lifestyle and see how these changes have affected your fitness and activity levels. See how your mood is affected by your sleep. Track lethargy against dreams, diet or any part of your daily life that you choose. Smart diary has all the features that you would expect to find in a professionally designed personal information manager. However, recent researches have reported that this research method is insufficient due to the quality of diaries collected from a group of volunteers. For developing smart diary app we use sensors which have the ability to collect data and information from the environment around us The data collected by sensors is usually incomplete, redundant fragmented, or incorrect. Various sensors equipped with smart phones are GPS, Accelerometer, proximity sensor, etc. By using the GPS sensor, we can get current information from the GPS receiver like latitude and longitude coordinates, bearing and speed. An accelerometer is a device which measures proper acceleration. With the rise of Internet, the form of diaries has undergone noteworthy changes. Online journals, micro blogs, Tweets, and Facebook status all contain nonstop Updates on a person's life events. Moreover, the complication of people's lives have increased dramatically due to the tight Intertwining of both "online" and "offline" lives. On the other hand, since more and more activities are attracting our attention, we have less and less time to note down the stories belonging to our unique life. It also provides data from verified sources for social studies. we suggest a an approach which is fully software-based to generate personalized diaries .Due to the widespread use of smartphones in recent years this approach has been adopted. Our main idea in this paper is that, as the user carries the smartphone, this device will be able to perceive the environment through sensors and infer users' behavior[6]. For example, user's life activities like. motion, SMS, phone call, etc. throughout a day, from which we can deduce many different types of user-interested actions and record them. The inference results are then summarized into human-readable forms example a diary. We name this application as "Smart Diary", as it is purely based on software, and does not require interference from user. Although the central idea

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of Smart Diary is quite simple, there are many challenges that we have to face to bring it into reality.Due to the battery limitations on the smartphone, it is usually not acceptable to keep the application active for long periods of time. Therefore, tradeoffs have to be made in terms of the amount of data that the application collects, and the precision that it achieves[3]. Specifically, we summarize the following challenges that our design faces:

1. Smart Diary has to report the challenge of user Secrecy as the dairies generated contain unique daily Actions of users, such as their entertainments, important social contacts, and health conditions, it is necessary to ensure that such information is not leaked to other people. This challenge is particularly urgent as recently exposed security loopholes have proven that it is possible for these phones to be hacked through hackers or NFC (near field communication)techniques.

2. We need a mechanism to support the personalization of Smart Diary, as each user has their own life styles and experiences. Different users may interpretate the same sensing readings in their own manners, leading to user-specific output in diary contents. The output from Smart Diary should reflect the user's personality, and consist of the most appreciated and interesting experiences, which can be different from user to user. In addition, the system's framework should be adaptive to the changing requirements of the users. we develop a variety of techniques to address the above mentioned challenges, and summarize their major contributions:

•We present a Smart Diary, a fully automatic software system that allows highly intellectual and human-centric generation of diaries based on the sensing readings from users' smartphones[5]. The app does not require human input as the whole process is flexible and customizable.

•To maintain the privacy and secrecy, we have to perform all recognition of activity and context inference on the phone side rather than on the centralized server, so that no data need should be transmitted over the Wi-Fi network. we present energy-efficient algorithms that adaptively classify user's activities based on sensed by sensors , based on which we are able to infer higher level events to achieve this goal.

•In order to fulfill the needs of different users, we present a sustainable mining model and extensible event mining model and the logic language for rule-based event inferences, where users can follow their own inference rules for higher level event generation. These rules are written in a logical manner, which make them easy to write and modify. We also develop a feedback mechanism so that users can also provide optional opinions on the generated diaries, so that the system can learn continuously over time to improve its diary generating abilities[4]. In the long term, we believe that this system we have developed will not only prove useful for people to recall their life events, but also will be very helpful for social studies where accurate user profiles of their activities are needed. Our evaluation results on Smart Diary illustrate that it has achieved its goals with reasonable performance.

II. LITERATURE SURVEY

a. Activity Recognition using Cell Phone Accelerometers:

In this paper they described how a smart phone can be used to perform activity recognition, simply by keeping it in ones pocket. They further showed that activity recognition can be highly accurate, with most activities being recognized correctly over 90% of the time. In addition, these activities can be recognized quickly ,since each example is generated from only 10 seconds worth of data. They have several interesting applications in mind for activity recognition and plan to implement some of these applications in the near future. [1]

b. Semantic Streams: A Framework for Compassable Semantic Interpretation of Sensor Data:

The framework presented in this paper provides a declarative language for describing and composing inference over sensor data. There are several benefits to this framework. First, declarative programming is easier to understand than low-level, distributed programming and allows common people to query high level information from sensor networks. Second, the declarative language allows the user to specify desired quality of service trade-offs and have the query interpreter execute on them, rather than writing imperative code that must provide the QoS. Finally, the framework allows multiple users to task and re-task the network concurrently, optimizing for reuse of services between applications and automatically resolving resource conflicts. Together, the declarative20 K. Whitehouse, F. Zhao, and J. Liuprogramming model and the constraint-based planning engine in our framework allow non-technical users to leverage previous applications to quickly extract semantic information from raw sensor data, thus addressing one of the most significant barriers to widespread use of sensor infrastructure today.[2]

c. Activity and Location Recognition Using Wearable Sensors:

Here we come to know that what sensor is giving us what input and in what way[3]. Using measured acceleration and angular velocity data gathered through inexpensive, wearable sensors, this dead-reckoning method can determine a user's location, detect transitions between preselected locations, and recognize and classify sitting, standing, and walking behaviors. [3]

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d. Activity Recognition from User-Annotated Acceleration Data:

This paper suggests that how the sensors take input in different ways from the user. It also suggests that a mobile computer and small wireless accelerometers placed on an individual's thigh and dominant wrist may be able to detect some common everyday activities in naturalistic settings using fast FFT-based feature computation and a decision tree classifier algorithm. [4]

e. A Framework of Energy Efficient Mobile Sensing for Automatic User State Recognition:

They used this paper to understand the energy consumption by the different sensors. Rich contextual information about users and their environment for higher layer applications and services is provided by mobile device based sensing. However, the energy consumption by these sensors, coupled with limited battery capacities, makes it infeasible to be continuously running such sensors. [5]

III. SYSTEM DESIGN AND OVERVIEW

We first present a high level view of SmartDiary and then elaborate those components in details in the following sections. The framework is shown in Fig. 1, which includes four layers: raw data collection, context analysis, event personalization, and diary generation. Through these four layers, SmartDiary captures important events according to users' preferences, and automatically generates diaries to the user.

A. Raw Data Collection:

Smart phones are equipped with a wide range of sensors, that provide an ideal platform for user's data collection. We are particularly interested in six representative data sources: motion activities, location data, app usage, calendar events, phone calls or SMSmessages, and web history.

a. *Motion Activity:*

We compare the performance of using accelerometer alone versus using accelerometer and gyroscope together,.to capture motion activities. Based on our inferences, we observe that it is sufficient to use accelerometer readings alone to infer users' activities such as driving, walking, sitting, and playing games.

b. *Location Data:*

The user's most visited places (such as office, restaurants, etc.) and commuting routes can be easily tracked by precise location readings[2].We use these locations to deduce the location context of users' activities.

c. *App Usage:*

The usage patterns of apps provide an attractive resource In order to identify a user's behavior, social activities and personal interest, the usage patterns of apps provide attractive resource. In our system, we record such activities over time to support dynamic inference of users' interest.

d. *Calendar Events:*

As an explicit resource that reflects users' schema, the events in a calendar usually give us the most direct insight on the user's life, such as their business meetings, friend parties, and travel plans.

e. *Phone Calls and SMS Messages:*

These information sources provide us with the users' "off-line" social group sand the interaction of the user with his/her friends via phone calls and SMS messages.

f. *Web History:*

History from the smartphone's browser helps Smart Diary to learn and analyze those topics that the user is interested in, and monitor how the users' personal preferences change with time.

B. Context Analysis

The context analysis layer takes the processed raw data collected in the lower layer as input, so that it may extract multiple types of events from the users' life. Each event is produced by a mining component, and we develop multiple types of mining components in the system. To better manage the reuse of resources, we propose a novel *sustainable mining model*, which decomposes a mining component's algorithm procedures into separate processing units. These units will continuously shuffle raw data, and provide the relevant ones to all the mining components where events are assembled. Specifically, we classify the events into three classes: entertainment activities, social activities, and health conditions. Processing of these events either adopts existing algorithms or relies on user-specific logic rules.

C. Event Personalization

However, the events extracted by the context analysis layer are purely objective. From the perspective of the users, however, some events are more meaningful than others. Event personalization, as its name suggests, allows Smart Diary to select those most interesting events for a user based on their preferences[1]. Two major modules are involved in this layer: the ranking module and the filtering module. The ranking module calculates the importance based on our three criteria, then ranks these events. The filtering module only provides those most interesting events as output, which are handed over to the next layer for diary generation.

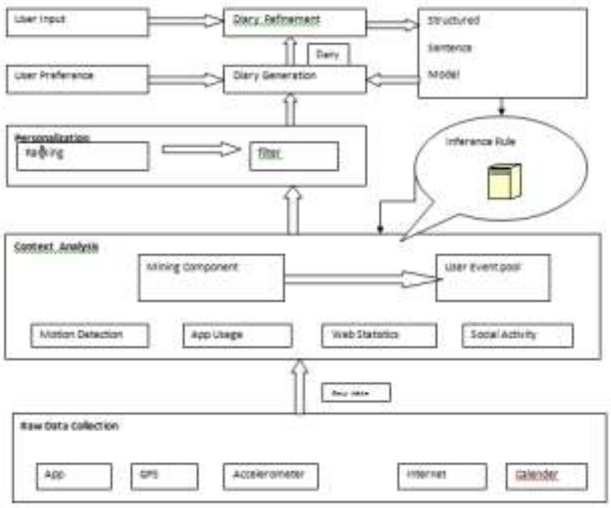

Fig 1.Framework of smart diary

D. Diary Generation

Given the personalized events, this layer translates the events into recognizable sentences. To facilitate this process, we develop a model called the narrative structured sentence model. One key feature of this model is that it uses regular expression formats to construct natural language sentence templates. During runtime, real event properties, such as the time of the day and the user's activities, replace these wildcards in the regular expression templates to generate diary outputs. Furthermore, to make language output natural, each type of events has multiple corresponding structured sentence templates for use. After diaries are generated, we also provide an optional step where the user may provide additional feedback regarding the generated diaries. For example, the user may want to share their sentence with other users or revise an existing sentence.In practice, this stage is not only useful for improving the quality of the diaries, but also for enhancing the narrative structured sentence model by adopting better structured sentences for each event. Note that the raw data like sensor readings and locations are not collected, the user's privacy concern has been preserved.

IV. RAW DATA COLLECTION

A smart phone is equipped with various types of sensors by which we can obtain heterogeneous data ranging from motion activities to location data. Among the various information sources, we choose the following types of sensors: the accelerometer, GPS location service, phone call history, SMS service, and app usage.Table I summarizes the types of raw data we collect to minethe user's behavioural patterns and daily activities. For instance, we use theaccelerometer and location data to deduce whether a user is working in his/her office or driving on the highway. In short, we are interested in the "when-where-who what" aspect for each event, namely, what the user is doing, who is involved in, where the event happens, and when it happens. The simplest way to retrieve raw data, is to survey the source directly and periodically. For example, to detect the current active app used by the user we can set up a timer. The raw data coming out from the diverse sources may not be exactly periodical (e.g. the accelerometer in Android OS does not sample in equal rate due to restrictions of the Android operating system), the mining component may need different sampling frequency, and the loss of GPS signal may unexpectedly happen. Hence , we propose a layer of *middle buffer* between the source and the raw data. Sensor source

TABLE I :THE RAW DATA DETAILS

Type	Details
Accelerometer	(timestamp, acc_x, acc_y, acc_z)
Location service	(timestamp, latitude, longnitude, speed)
Phone call/SMS	(timestamp, incoming no, outgoing no, duration)
App usage	(timestamp, app_name, duration)

often updates the readings in the middle buffer's memory, while the independent timers trigger the data collection on their own schedules. The collected data returns the most recently measurement. when data sources are unreliable this middle buffer is especially used: for example, if smartphone loses the GPS signal in an indoor atmosphere, as long as the user does not walk out of the building, their location is still recorded as the last GPS update as they move in the building because the middle buffer has not been changed. In such a way, we can still use the last updated data when the sensor is not responsive and we can sample the data in different frequency. Initially we used both accelerometer and gyroscope in our study to detect motions. We gathered 7 user's motion sensor data for about 1 month and asked them to label their motion activity. Then we used the first half of the data to train our classifier, and use the rest of the data to test it. We calculated the standard deviation features of both accelerometer and gyroscope instead of using the original data values .Based on the experimental study, shown in Table II, we conclude that using the accelerometer alone is enough even though using both accelerometer and gyroscope sometimes achieves a slightly higher precision. The gyroscope's sampling rate is much higher than the accelerometer, leading to much redundant data, which explains why there is only a 3% of accuracy increase. On the other hand, keeping the gyroscope on will drastically increase the energy overhead. Therefore, we make the trade-off by only reading the accelerometer.

V. CONTEXT ANALYSIS

A. *Rule-Based Event Inferences*

There are some MCs implemented based on existing algorithms, users also need to specify flexible event processing rules that handle multiple types of activities in users' lives. Hence, we develop a model of rule-based event inference. Rule-based inference is based on a language grammar which is similar to logic programming, such as Prolog. The language used in Rule-based inference adopts logic symbols to connect results between mining modules. An example of the logic language to deduce an event, we use *Consider an example of shopping event.* If this user's location belongs to a shopping center or a mall, the motion is mostly walking, the day is not Monday or Tuesday, and the duration is longer than a threshold, say, 10 minutes then user is considered as shopping. On the basis of this we can write the following logic rule to infer the event:

Shopping (User, Day) :-
Member (Location, ["mall", shopping center"]),
Motion is "Walking",
Duration < 600,
Not member (Day, ["Monday", "Tyesday"])

VI. EVENT PERSONALIZATION

Though the context analysis layer continuously extracts events depending on sustainable mining model, all of them are not required to be included in the final output of the diary for two reasons:

a. The number of events can be huge because of the large number of mining components which will lead to bloated output along with redundant information.
e.g: 50 sentences about the motion activity throughout the day.

b. Each user may have a different taste based on diary content and length, and he may not want to adopt the same template. Therefore such preferences have to be taken into consideration by diary.

For giving preferences we use Event Filter algorithm:

Algorithm I Event Filter Algorithm

Input: the event sepuence: events.
Input: The user's preferred length k.
Output: Top k event candidate.
Initial candidate <- min heap.
For all e in events do
If candidate.size< k then
Candidate.insert(e)
Else if e.rank>candidate.top()
Candidate.insert(e)
Candidate.pop()
Return candidate

VII. DIARY GENERATION

A. *The Narrative Structured Sentence Model*:

Here we describe the diary generation layer. Essentially, the problem is a variant of natural language processing (NLP)problem (e.g. "speech transcription"), except that here the signal source is not from the speech, rather it is from the events generated by the personalization layer. The traditional ways to handle the NLP problem can be divided into two categories: first is based on statistical methods, and the second is based on language grammar rules and semantics. However, none of the two approaches fit our problem well for the following reasons:

1. The statistical NLP solution requires explicit data features to perform the classification tasks. Usually it needs a huge set of data (in GB size) to support the training phase for tasks which are complex, so that the output can be efficient. In the Smart Diary case, the source is a series of data which are inherently costly to collect (which requires deploying smart phones to a large population over an extended period of time). Therefore, it is difficult to build a large training data set.

2. The second NLP approach is based on analysis of huge amount of annotated data to achieve precision. However, with the limited memory and battery capacities of smartphones, we find this approach not suitable either. Therefore, we decide to follow an alternative approach where the events are directly translated into language through a novel and lightweight narrative structured sentence model. The structured sentence model works as follows. It takes the events generated from the previous layer as input, and chooses a pre-defined sentence template from a candidate list for this particular event. This sentence template comes with a list of sensitive fields that wait to be filled, which are represented by globally distinctive symbols. In other words essential fields of information are sensitive fields whose real values are decided in the diary generation step. As an example, we take a look at the following sentence:
Structured Sentence:

Template: You and * know each other so well that you made % calls and spent an average of % minutes on each call. Generated Sentence by Smart Diary: You and harsh know each other so well that you made 20 calls and spent an average of 55 minutes on each call.

VII. CONCLUSION

In this we have discussed the motivation, plan, implementation and estimation of Smart Diary, an integrated sensing framework that integrates mobile data analysis, human activity inference, and natural language processing on the smart phone platform. Our preliminary evaluation results on the working prototype are thrilling. We have demonstrated that the system works as desired in that it may infer people's daily life devotedly and generate dairies automatically and flexibly according to user's preferences. In the future, we hope that this app can further expand the types of MCs by adding more inference rules, develop more possible ways to display man's daily activities, and make the sensing framework to be publicly available

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