Smart Diary: the Narrative of Your Daily Life

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***Abstract*—In this paper, we present *Smart Diary*, a novel application integrating mobile sensing, activity inference, and natural language processing to facilitate novel knowledge representations of sensor data. Smart Diary records and analyzes a person's daily life and transcribes those activities into human-readable outputs referred to a diary. Smart Diary makes four key contributions. First, to our best knowledge, Smart Diary is the first attempt to represent human-centric daily life through a narrative process. Second, we propose a lightweight and practical working flow in a bottom-up manner, through which we make inferences and generate diaries. Third, we present two novel models in solving context analysis issues, namely, the *sustainable mining model* and the *narrative structured sentence model*. Finally, we develop an accurate and efficient personalization/filtering algorithm in this paper so that the diary is both concise and informative.**

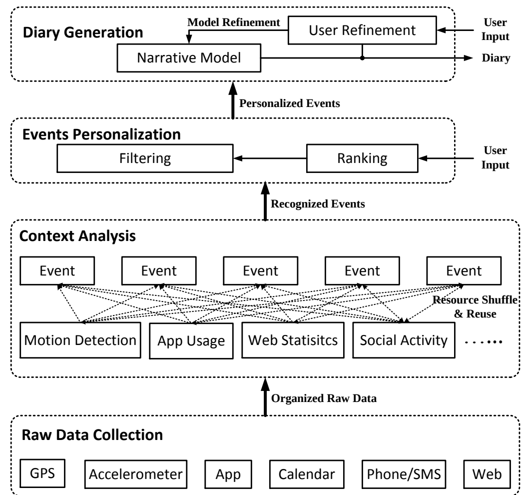


Fig. 1. Framework of Smart Diary

I. Introduction

A personal diary may record the person's experiences, thoughts, feelings, even comments on events in daily life. Some personal diaries, such as those by Anne Frank, become well read books and the basis of plays and films. With the emergence of the Internet, the form of diaries has undergone significant changes. Online journals, blogs, micro-blogs, twitters, and facebook status all contain continuous updates on a person's life events. Moreover, the quantity of personal daily events increases hugely when interweaving both "online" and "offline" life. With more and more activities attracting our attention, unfortunately, we have less and less time to write down those trivias belonging to our unique life. For example, you are probably over active in others' life by catching up with their facebook or twitter updates, leaving comments and "like it", but may not have paid enough attention to write down your own experiences.

In the second scenario, researchers in social science sometimes rely on participants' diaries to carry out various studies. However, they complain about the quality of the collected dairy documents [2]. The contents are frequently missing, and the low retention rate may mess up the study. Furthermore, the diaries from the participants may not cover the expected contents because different people have distinct understandings. The researchers have to make the requirement as simple as possible, making the data collection process particularly difficult.

This paper represents a departure from conventional approaches of writing diaries, and explores a possible architecture based on the widespread adoption of smartphones to generate diaries automatically. The core idea is simple: consider Bob who always carries a smartphone with himself. The phone then becomes his companion, meaning that it will capture all the events with Bob together. As smartphones are typically equipped with a wide range of sensors, they can sense the moments that Bob experiences, infer the contextual activities, summarize the measured data, and translate those data automatically into the diary form at the end of the day. Naturally, we call this service *Smart Diary*.

II. Methodology

To make our vision come true, we meet a number of challenges. The major ones include: first, we must continuously collect heterogeneous raw data, ranging from motion sensor readings to app usage statistics. Second, the raw data does not mean anything until we define what context information is needed and how to retrieve them. Third, as the users have different taste, preference, and reading experience, we should personalize information extracted from the context. Fourth, the diary is presented in the natural language, so it requires a special model to narrate the raw data so that the outcome can be presented in a natural language instead of "alien" digits.

The following section is arranged in this way: we first propose the overview of the system framework in section II-A, and we address the challenges above from section II-B to II-E respectively.

A. System Framework

The framework shown in Figure 1 includes four layers: raw data collection, context analysis, events personalization, and diary generation from bottom up, which are corresponding to the four challenges. The core idea is that we analyze the raw data and discovery interesting events of a person (e.g. social activity), then rank the user's favorite ones. Thereafter, we transcribe each event into a single sentence which embodies the whole meaning of the event.

B. Raw Data Collection

In this layer, we obtain comprehensive user profiles through the following data sources: first, *motion activities* as measured by accelerometer readings, providing us with information about the user's motion activities such as driving, walking, sitting, and playing games; second, *location information*, which offers us opportunities to find the user's personal places, commuting routes, and working locations; third, *app usage*, which helps us identify a person's behaviors, social activities and personal interests; finally, the *phone call/SMS history*, which leaves hints on the user's "off-line" social groups and real-life connectivity.

C. Context Analysis

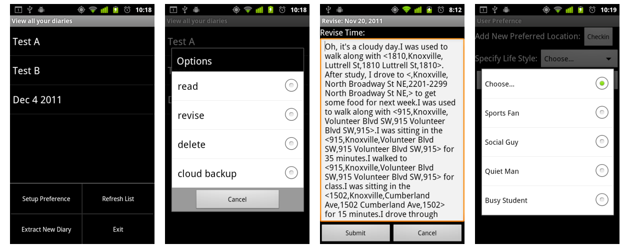
The context analysis is a layer that is used to extract many different types of knowledge from raw data. As the user's expectations are dissimilar and unpredictable, it is hard for us to generalize data mining rules to represent users' life styles. Therefore, we propose a novel model called the *sustainable mining model* that decomposes a mining component (e.g. social activity) into several unique resource units. The resource units perform singular extracting tasks such as motion detection from accelerometer data, among others. Those resource units are shared with all mining components to reduce the system complexity and redundancy. If a new mining component is added, we only need to implement the extra resource units that do not currently exist. The output of context analysis will be those events generated from the respective mining components.

D. Event Personalization

The event personalization layer, basically, ranks the user's most interesting events. Two major modules are involved: ranking and filtering. The ranking module relies on the inherent importance among events (e.g. frequency and entropy) and user preference to assign scores. Then the filtering module runs a fast and memory-saving algorithm to select all the candidate events. Finally, the filtered events are handed over to the diary generation layer.

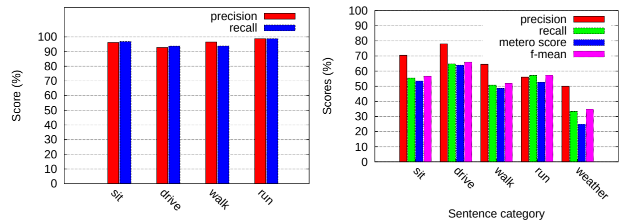
E. Diary Generation

Given the personalized events, in this stage, we generate diaries by mapping the events to sentences. The process model, specifically called the *narrative structured sentence model*, has a dictionary of sentences, each of which expresses the same meaning as the event does, but having some fields replaced by wild cards. Each wild card symbol corresponds to a field of information in an event (e.g. time and numbers) so that the event's information can be filled back into the sentence to form a complete sentence. Multiple structured sentences can be used for one event because an event's meaning can be expressed in multiple ways.



(a) main screen (b) user options (c) diary output (d) user preference

Fig. 2. The user interface screenshot of smart diary



(a) The motion activity recognition performance (b) The language quality score

Fig. 3. Preliminary performance results.

III. Preliminary Results

We implement the system on the Android smartphone and have obtained some preliminary experiment results. Figure 2 illustrates the user interface on the smartphone.

In addition, we evaluate the performance of our motion activity inference and the language quality of the diary. Figure 3(a) shows that the motion activity recognition has a very high precision/recall value, which indicates the small errors in the diary generation. Figure 3(b) uses the METERO [1] score as an objective measurement to evaluate the language quality. As is shown, the highest value of the METERO score is 65, which is not extremely impressive. However, considering the experiment is conducted in a small scale, we expect better results with larger scale deployments.

IV. Ongoing Work

Currently, we are focusing on the following aspects:

- **Adequate Raw Data Collection**: we are recruiting volunteers to carry out the experiment, but it usually takes several monthes to gather enough and high quality data so that our machine learning algorithm can be most effective.
- **Empower the Sustainable Mining Model**: the sustainable mining model is a plug-and-play model, so we are defining more interesting events to capture the user's daily life and integrate them into the model.

References

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