Smartphone-Based Lifelogging: An Investigation of Data Volume Generation Strength of Smartphone Sensors

Smartphone-Based Lifelogging: An Investigation of Data Volume Generation Strength of Smartphone Sensors

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Abstract. The lifelogging enable people to digitally record information about their daily life events for a variety of purposes including human memory augmentation. However, the lifelogging systems have several challenges regarding capturing, managing, semantic analyses, indexing, and retrieval of error-prone and noisy data produced by the sensors. The ubiquitous nature and technological developments makes smartphone as de-facto lifelogging device. The smartphone integrates a rich set of sensors, which provide unique opportunities for capturing contents and contextual information into a comprehensive lifelog archive. However, the continuous use of sensors can generate large amount of data that could raise problems for smartphone-based lifelogging systems. In addition, insight understanding of smartphone sensors data generation strength is needed for effective smartphone-based lifelogging systems development. These estimations will also help in understanding of smartphone sensors capability of fulfilling lifelogging systems objectives. To fulfill objective of this paper, an Android based application namely Sensors dAta Volume Estimator (SAVE) is developed using a proposed architecture. The SAVE utilizes smartphone sensors to capture and estimate sensors data from different real world scenarios. The results indicated that smartphone sensors can generate significant amount of data that can create storage, retrieval, and battery power issues for smartphone-based lifelogging systems.

Keywords: Smartphone · Sensors · Lifelogging · Personal big data · Information overload · Memory augmentation

1 Introduction

Acquiring and keeping of valuable information is a fundamental property of human behavior. However, unfolding users' lives could generate large volume of information resulting into information overload problem that could make storage, organization, and retrieval of information increasingly difficult [1]. Lifelogging is *"a form of pervasive computing, consisting of a unified digital record of the totality of an individual's experiences, captured multi-modally through digital sensors and stored permanently as a personal multimedia archive"* [2]. Personalized lifelogging systems are augmented memory applications, which would ease people by automatic and continuous recording

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and storing of a person's life events information [3]. Lifelogging devices/systems have used sensors for capturing information about peoples and their contexts/environments, and forward the captured information to a backend server/PC for storage and retrieval. However, most of the lifelogging devices were custom-built devices or applications relying on external sensors [4].

Smartphone is the highly ubiquitous computing device that is formed by combining the features of mobile phones and personal digital assistances (PDAs). Smartphone is becoming the commonplace and its popularity can be measured from its presence in the pocket of almost every individual today [5]. It is our constant companion due to being with us all the time and has the potential to know us very well beyond our imagination [5, 6]. A smartphone integrates enormous capturing and computing capabilities in a single jacket and making it a de-facto lifelogging device [7, 8]. A smartphone integrates a rich set of built-in specialized physical, logical, and informational sensors, which extends it capability than sensors found in dedicated commercial wearable lifelogging devices (e.g., SenseCam, etc.) and the list is likely to increase in the near future [9]. The smartphone sensors can be advantageous over commercial wearable sensors and devices [9, 10]. The sensors enables smartphone to continuously and unobtrusively capture information about us and our contexts and environments, and use the captured information as contextual cues to augment our episodic memories [10]. For example, smartphone based lifelogging systems can employ different sensors such as motion sensors (i.e., accelerometer and gyroscope), positional sensor (i.e., GPS), acoustic sensor (i.e., microphone), optical sensor (i.e., camera), biomedical sensor (i.e., heart rate), etc. to capture information into a lifelog [11]. The applications of smartphone sensors for lifelogging are shown in our previous research work [9]. However, the number of sensors used depends on the types of lifelogging. A focused lifelogging (e.g., activity monitoring for self-quantified analysis) would use one or two sensors sufficiently to capture information about some aspects of a person's life experiences but extreme lifelogging would require using of a number of sensors to capture lifelog information as complete picture of life experiences as possible [12].

The storage capacity is increasing with the increasing demand of lifelogging, as indicated by the Kryder's Law [13]. The smartphone storage is also increased and smartphone with 256 GB storage is commonly available, which is enough to store images for more than 3 years if taken with a frequency of 1.65 million images per year [12]. The processing power is increased and smartphone with quad core processor are commonly available. The networking technologies are improved and massive amount of data can be received and transferred wirelessly from a smartphone. The smartphone sensors can generate tones of information (e.g., accelerometer can generate up to 21 million readings per year if operated at the lowest 1 Hz frequency) for rich lifelogging. Despite of advancements, the storage, managing, analyzing, indexing, and retrieval of stream of multimodal information from the noisy, error-prone, and gaps in continuity, etc., smartphone sensors data can poses serious challenges for smartphone-based lifelogging [14]. Furthermore, storing massive amount of unusable sensory data would be wastage of storage and resources from researchers' point of view. Therefore, researchers are interested in finding and storing patterns in continuous stream of multimodal sensory information instead, that is enough to effectively diagnose and describe user experiences in real time. However, to lay down effective criteria for recognition and selection of sensory patterns, a thorough investigation of smartphone sensors is essential to determine their strength, weaknesses, and reading speeds in real-world scenarios.

In this paper, we have investigated for detailed estimations and analysis of data volume generation strength of smartphone sensors for lifelogging. To support objective of the paper, an Android app namely Sensors dAta Volume Estimator (SAVE) is developed to automatically monitor, record, and analyze data volume generated by smartphone sensors. during daily life activities. A comprehensive test bed has been defined that is consisting of tests for estimating of sensors data volume captured during different daily life activities in different real-world scenarios. The results have indicated that smartphone sensors can generate huge personal big data (i.e., lifelog) due to their sampling frequency rates and inherent working mechanisms.

2 Lifelogging: History and State-of-the-Art

The history of personal lifelogging research area starts from the publication of Vannevar Bush's famous article "As We May Think" in 1945. He suggested an imaginary mechanized device called Memex (Memory Extender) [15] that will act as human memory prosthesis and will optimize humans' lives by increasing peoples' ability to record, organize, search, and exchange the massive amount of information generated during their daily lives experiences. Bush described Memex as "enlarged intimate supplement to one's memory" whose technical interpretation hints for the first lifelogging system [12]. Years later, the introduction of advanced digital technologies enabled the release of several manifestations based on the idea of recording all of a person's life time experiences in visual and audible formats by using cameras and microphones. Steve Mann (father of wearable computing) coined the idea of wearable computing and developed increasingly smaller wearable devices with innovative increasing sensing, capturing, and displaying hardware components for manipulating lifelog information and enjoyed the media status as "the world's first cyborg" [16]. To solve several of the fundamental problems in wearable lifelogging technologies, Steve Mann invented several generations of wearable camera technologies from early personal imaging to the EyeTap system [16], which could be viewed as precursor of Google Glass. Later researcher demonstrated using of high valued sensors for capturing and identifying of a complete set of contexts types (e.g., using GPS for location, etc.) to be used either as a trigger to capture pictures or as metadata for indexing and retrieval of the visually captured data [17]. A number of cheap wearable commercial products are also available in the market for monitoring certain aspects of a person's life such as SenseCam, Vicon Revue, Narrative Clip, Fit Bit One™, Nike FuelBand™, and Lark™. They are composed of combination of basic sensors (i.e., accelerometer, magnetometer, gyroscope) to monitor and log activity levels (e.g., steps count, distance travelled, and caloric output) on-board and subsequently forwards the captures wirelessly to a cloud service via laptop or PC.

The ubiquitous computing devices showed their importance in lifelogging because occurrence of many significant activities and events cannot be restricted to a particular schedule or location. Smartphone allows lifelog systems by offering new opportunities to unobtrusively record nearly all aspects of a person's life to construct a digital memory [18]. Smartphone based lifelogging applications can exploit its rich sensing capabilities for determining contextual cues to effectively depict peoples' daily life activities and events such as where we go, what we do, who we interact with, what information we consume, etc. Nokia Lifeblog project [19] was the earliest smartphone based lifelogging application. Nokia Lifeblog inspired many research efforts in both industry and academia which resulted into emergence of a new breed of lifelogging applications that showed feasibility of integrating more and more sensing and logging functionalities such as Pensevie [14], MyExperience [20], UbiqLog [8]. SenseSeer [6], Digital Diary [21], and Experience Explorer [22], etc. Each of these systems have used a bunch of smartphone sensors for capturing specific contents and contextual information as per their idea and requirement. However, none of them has provided any insight to the smartphone sensors data generation strength.

3 Methodology

This paper focuses on presenting a methodology for gaining insight knowledge of data volume generation strength of smartphone sensors for lifelogging. An explicit architecture is proposed to effectively estimate, record, and analyze the data volume generated by each sensor explicitly and in combination with other sensors. The proposed architecture is composed of three layers: interface layer, processing layer and physical layer as shown in Fig. 1. Each layer is composed of several sub-components that exploit the capabilities of the layer below. A precise description of each of the layers is presented in the following headings.

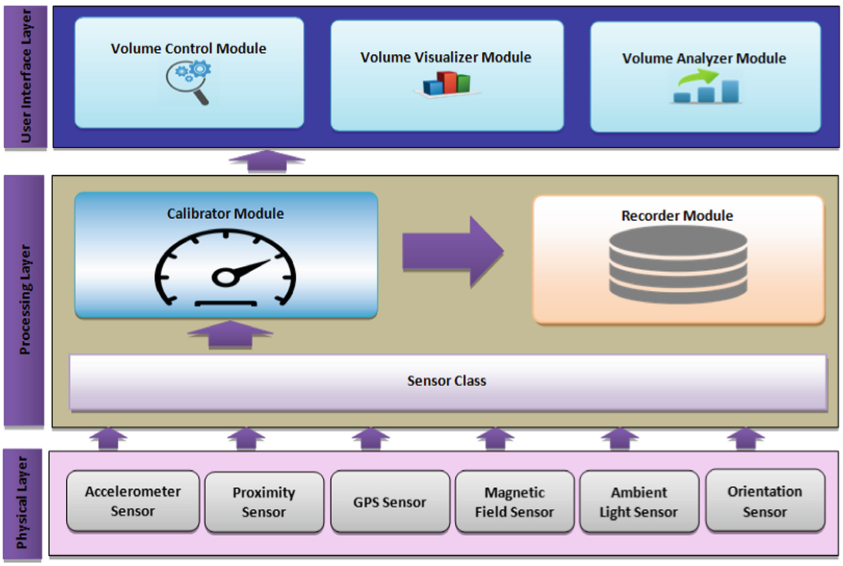

Fig. 1. The proposed architecture.

3.1 User Interface Layer

User interface is the space where users interact with the system. The user interface is easy to use, easy to understand while having lower learning curves, having professional aesthetics, and requiring minimum steps to obtain the desired results. User interface layer is composed of three modules including volume control, volume visualizer, and volume analyzer. The volume control module is responsible to adjust a sensor reading frequency and time interval between consecutive readings to minimize and maximize a sensor's data volume generation speed. The volume visualizer module displays a sensor's readings as well as maximum and minimum frequencies, maximum and minimum interval between readings, and data volume per reading. The volume analyzer module is responsible for displaying each sensor accumulative data volume with per second time stamp.

3.2 Processing Layer

Processing layer encompasses all of the technical operations. Processing layer is composed of three modules namely sensor, calibrator, and recorder. The sensor module accesses the physical layer for retrieving data from the sensors and processes the captured data. The calibrator module adjusts the reading rate of a sensor as per instructions from the user interface layer. The recorder module is getting sensors data from the sensor module and stores it in a local database along with reading frequency and time interval information from the calibrator module. The flow chart of calibrator module and recorder module are show in the Figs. 2 and 3 respectively.

3.3 Physical Layer

The physical layer encompasses Android's built-in sensors and storage capabilities and uses Android's libraries (i.e., SensorManager, etc.) to turn sensors on/off, adjust the sensors reading frequencies, and store the data generated by the sensors. SqlLite is used by the recorder module for creating database to store sensory data and associated data for analysis purposes. From SqlLite, the database can be imported to PCs for conducting more detailed and powerful analysis using applications such as MS Excel, etc.

4 SAVE Implementation and Sensors

Using the architecture, an Android-based application namely SAVE is developed. The SAVE is aimed running with Ice Cream Sandwich 4.0.3 or higher and is developed using Android SDK tools revision 22.6.3 with Eclipse IDE and SensorSimulator-2.0-RC1 running on a desktop machine. The target code is mainly deployed and tested on Samsung Galaxy SIII running with Android Jelly Bean 4.1.1 operating system. Figure 4 represents snapshots of SAVE user interface. The data volume generated by a sensor is calculated using formula shown in Eq. (1) where TV represents the total volume, US represents unit sample size of a sensor (e.g., accelerometer generates 12 bytes data per sample, and GPS generates 24 bytes per sample etc.), T represents the total usage time of a sensor, and S represents the number of sample taken by a sensor within the T. Reading frequency (F) of a sensor is the no of readings (N) per second (Sec) as shown in Eq. (2). Number of samples (S) of a sensor depends on the reading frequency (F) of a sensor and the time interval (TI) between consecutive samples as shown in Eq. (3). In current version of SAVE, the sensors, which are available in most of the smartphones are used to validate and execute our tests. The sensors used are:

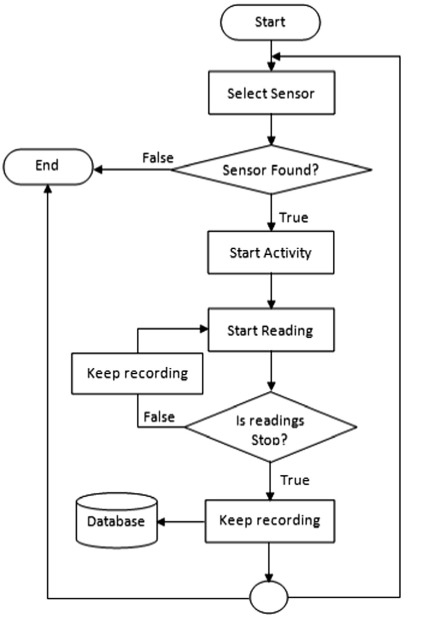

Fig. 2. Flowchart of calibrator module

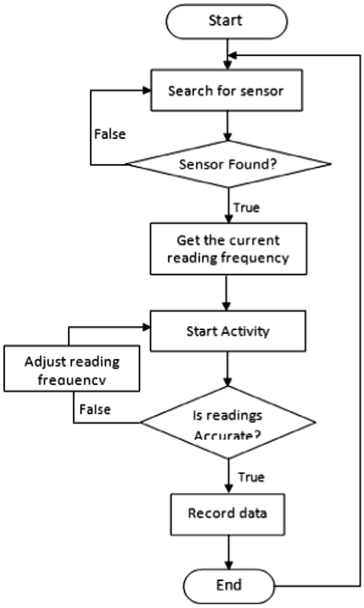

Fig. 3. Flowchart of recorder module.

$$TV = US \times \sum (T \times S) \tag{1}$$

$$F = \frac{N}{Sec} \tag{2}$$

$$S = \frac{F}{TI} \tag{3}$$

4.1 Accelerometer Sensor

The tri-axial accelerometer sensor can have maximum reading frequency of 102 Hz and minimum reading frequency of 1 Hz or 2 Hz. The data volume generated by each accelerometer sample is 12 bytes. In case of maximum frequency (i.e., 102 Hz), accelerometer could generate data volume of 1224 bytes/sec and 105.75 MB/day. Furthermore, if accelerometer's data is collected for a year continuously, it could generate data up to 38 GB per year. However, generating such a huge volume of data raises questions related to storage and retrieval of specific patterns of data for smartphone-based lifelogging applications.

4.2 Orientation Sensor

The orientation sensor can have minimum reading frequency of 1 Hz and maximum reading frequency of 8 Hz. The data volume generated by each orientation sensor sample is of 12 bytes. Due to having low reading frequency, the data volume generated by a smartphone orientation sensor is much less as compared to accelerometer sensor. If orientation sensor's data is captured continuously with its maximum reading frequency, the total data volume generated could grow up to 3 GB per year.

4.3 Magnetic Field (MF) Sensor

The MF sensor continuously read data from its surroundings to recognize the NORTH for defining directions. Like orientation sensor, the MF sensor can have minimum reading frequency of 1 Hz and maximum reading frequency of 8 Hz. The data volume generated by each sample is 12 bytes. Therefore, like orientation sensor, the MF can generate maximum of 3 GB data, if used continuously for a year.

4.4 Proximity Sensor

The proximity sensor is event based sensor and captures data upon the occurrence of a target event. It has been observed that proximity sensor's reading frequency cannot be customized as per needs. The maximum reading frequency is 4 Hz and minimum reading frequency is 0 Hz and the data volume generated by a sample is 12 bytes.

4.5 GPS Sensor

The GPS sensor is used for users' localizations by receiving signals from satellites. The GPS sensor is event based sensor and updates location coordinates (i.e., latitude and longitude) by receiving signals from satellites accordingly. The GPS sensor reading frequency cannot be customized as per need. However, the maximum reading frequency is 1 Hz and minimum reading frequency is 0 Hz and the data volume generated by a reading sample is 24 bytes.

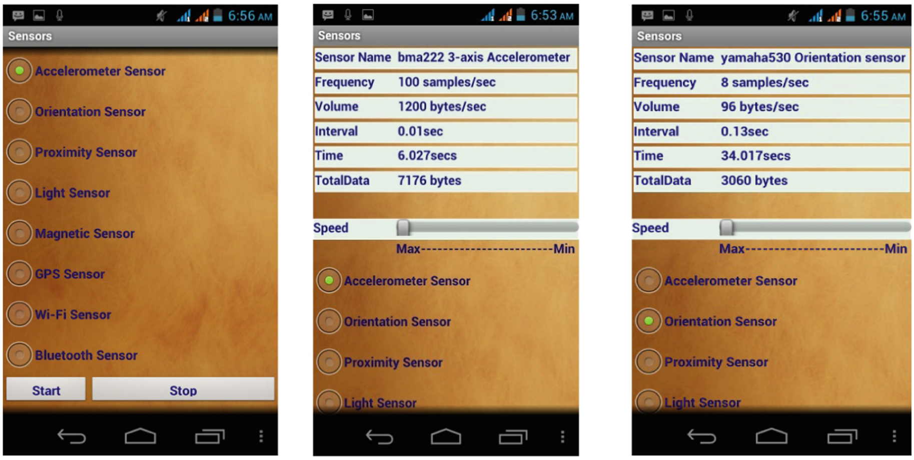

Fig. 4. User interfaces of SAVE.

4.6 Ambient Light Sensor

The ambient light sensor is event based sensor and reads data from environment with changes in the light intensity. It has been observed that ambient light sensor reading frequency cannot be customized. The maximum reading frequency is 1 Hz and minimum is 0 Hz and the data volume generated by a reading sample is 12 bytes.

5 Results and Discussion

For accurate estimations of data volume generated by smartphone sensors, SAVE was used in real-world scenarios. To fulfill objectives of the study, a comprehensive test program was designed to collect sensors data while performing daily life activities in different real-world scenarios (i.e., walking, driving, playing games, working in office, etc.). However, the activities and their durations were not consistent and dependent on the testing scenarios and test cases. All of the activities were performed uniformly and randomly for a period of two hours during a scenario test. To carry out tests, three participants were voluntarily selected from the junior researchers in the Department of Computer Science, University of Peshawar. All of the participants were given Samsung Galaxy SIII smartphones installed with SAVE and they were trained how to use SAVE. Furthermore, the participants were instructed to perform all of the daily life activities uniformly and randomly for a period of two hours for a week to collect maximum data out of each sensor. The sensors data collected from each sensor after performing all of the tests were analyzed and results were compiled. The details of the sensors data generated by the sensors along with their time intervals and minimum and maximum frequencies are also shown in Table 1. Analysis of the data collected from sensors showed that accelerometer, orientation and magnetic field sensors were generating huge amount of lifelog big data. Our results revealed that sensors lifelog big data volume will increase exponentially with the passage of time while recoding the daily life activities/events. This exponential increase in volume will lead to storage limitation problem because the memory size (e.g., 128 GB) would be very much less to store the data generated by a single accelerometer sensor for 5 year (i.e., 38 GB data/year). However, if we got succeeded in storing such a great amount of data by using any method, searching a specific pattern of data will be a resource intensive and cumbersome task, which could result even in completely jeopardizing the underlying smartphone platform.

Table 1. Data volume generated by the smartphone sensors in the testing scenarios.

Sensor Name	Interval		Samples/second		Volume/sample in Bytes	Total volume/year	
	Minimum	Maximum	Minimum	Maximum		Minimum	Maximum
Accelerometer	0.01 s	0.6 s	1	102	12	373.248 MB	38.07 GB
Orientation	0.12 s	0.6 s	1	8	12	373.248 MB	2.98 GB
Magnetic Field	0.12 s	0.6 s	1	8	12	373.248 MB	2.98 GB
Proximity	Not determined	Not determined	0	5	2	0	1.86 GB
GPS	Not determined	Not determined	0	1	24	0	746.49 MB
Ambient Light	Not determined	Not determined	0	1	12	0	373.24 MB

6 Conclusion and Future Work

The smartphone-based lifelogging systems require proper management of sensors and sensors data. The investigation of the data generation strength of smartphone sensors is provided in this paper for smartphone-based lifelogging systems. An Android-based application (i.e., SAVE) is developed using proposed architecture to accurately capture and analyze the data from the smartphone sensors. After performing the tests, the results indicated that smartphone sensors can produce huge data volume of contents and contextual information for the smartphone-based lifelogging systems. The sensors data generation strength depends on their sampling frequency rates and inherent working mechanisms. Comparatively, sensors with continuous data capturing nature are found much data prone as compared to event-based sensors. Furthermore, sensors with high reading frequencies can generate huge amount of data in a short span of time. Generating more and more sensors data is advantageous for accurate measurement and presentation of tiny changes in the measuring phenomenon and determining the states and contexts of a user. However, it would raise battery power, storage, and retrieval problems for the smartphone-based lifelogging systems. The storage of voluminous data either form a single sensor or from multiple sensors would be significant because the storage provided by the smartphone is too less even to store the data generated by a single sensor for a few years. However, if methods are investigated for storing voluminous sensors data in limited storage; other issues (e.g., indexing, searching, and retrieving specific patterns of data) would pose resource intensive and cumbersome tasks, which could jeopardize the underlying smartphone platform and quickly drain out the battery power.

In the future, we are interested in finding methods to detect users' states and dynamically adjust a sensor's reading frequency and time interval according to users' activities and contexts/environments. This would enable a smartphone-based lifelogging application to proactively control and adapt sensors' reading frequencies based on user daily life events patterns. The dynamic adjustments would not only help in reducing the sensors data volumes but would also help in solving the associated problems.

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