Health Drive: Mobile Healthcare Onboard Vehicles to Promote Safe Driving

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Abstract

This paper proposes Health Drive, a novel mobile healthcare platform with context-aware multiple-sensor integration to promote safe driving. Health Drive employs a multi-tier vehicular social network (M-VSN) architecture that consists of three tiers: network tier, mobile device tier and cloud tier. The network tier provides communication supports, and the mobile device tier works in parallel with the cloud tier to integrate and interpret diverse sensing data. The three tiers work together to provide a seamless solution that can efficiently collect and interpret diverse sensing data in the heterogeneous environments found in vehicular networks, to deliver personalized service to drivers for safety improvement in real-time. We evaluate the system performance of Health Drive and provide results of practical experiments to show the desired functionality and feasibility of Health Drive in the real-world for safety improvement in transportation.

1. Introduction

According to the statistics of World Health Organization (WHO), 1.2 million people die and 50 million people are injured or disabled on roads every year, and such unsafe road traffic condition is increasing and seriously harming global public health and development [1]. Also, WHO contends that the current level of road traffic injury is largely avoidable through promoting safe driving behaviors, such as avoiding fatigue driving, discouraging drinking and driving, and discouraging speeding.

With the development of mobile computing, cloud computing and worldwide deployment of mobile networks, current mobile devices such as smart phones can work with customized cloud computing platforms to provide emerging and pervasive healthcare applications to people anytime and anywhere. A number of research works have demonstrated that applying mobile healthcare to intelligent transportation system (ITS) could potentially prevent traffic accidents and promote human society significantly [2].

Currently, a variety of mobile healthcare solutions have been proposed for safety improvement in vehicular application scenarios, such as V-Cloud [3] and seeded cloud [4]. Most of them focus on the long-term health monitoring of vehicular users, or only consider the real-time traffic situations to avoid traffic accidents [5]. However, many research works have identified that for the time-sensitive and complex environments of vehicular safety applications, multiple factors like driver status and driving environment must be taken into account as one whole system for more effective safety systems [6]. For example, studies show that approximately 10% to 20% of all traffic accidents are due to drivers with a diminished vigilance level [7]; and the vigilance level not only depends on the health status of the drivers, but also the specific road conditions (i.e., under certain health status, a driver may react fast enough in a suburban district but needs a better status when driving in urban areas) [8].

Thus, a seamless solution that can collect and interpret data from multiple sources (i.e., healthcare data, vehicular operational data and dynamic traffic data) simultaneously in an efficient and effective manner from mobile devices is needed but has yet to be developed. Such a solution is important as it can help to improve drivers' safety through applications running in popular mobile devices they carry daily. There are several challenges that need to be addressed for developing such a solution, such as the heterogeneous service requirements and preferences of vehicular users (which may depend on the drivers' age, sex, and ethnic origin) and different versions of operating systems (OSs) of mobile devices (i.e., Android, iOS, Windows Phone) on aboard vehicles [9]. There is no specific mobile healthcare application that can fully meet such requirements and conveniently be used by different drivers [6]. Consequently, a seamless and effective solution that could widely facilitate real-world deployment of different customized mobile

1530-1605/15 $31.00 © 2015 IEEE
DOI 10.1109/HICSS.2015.371

healthcare applications to promote safe driving in transportations still needs to be investigated.

This paper fills the gaps identified above by proposing Health Drive, a novel mobile healthcare platform which employs a multi-tier vehicular social network (M-VSN) architecture to extend mobile healthcare to vehicular environments and to support the deployment of context-aware mobile healthcare applications for safe driving. Our major contributions are summarized as follows:

• We present the overall architecture design and practical implementation of Health Drive. The M-VSN architecture of Health Drive provides a generic architectural model, which consists of the first seamless solution to collect and interpret data from multiple sources on mobile devices, to deliver personalized healthcare service to drivers for safety improvement in transportations.

• We deploy and evaluate Health Drive through a set of real-world scenarios which not only verify the feasibility of Health Drive for real-world deployment but also provide practical experience.

The organization of the rest of the paper is as follows. Section 2 reviews the background of related techniques and concepts of Health Drive. Section 3 presents the M-VSN architecture of Health Drive consisting of three tiers: network tier, mobile device tier and cloud tier, and discusses how they address the challenges of healthcare for safety improvement in vehicular networks. Section 4 shows application examples of the proposed Health Drive platform. Section 5 evaluates the system performance of Health Drive. Section 6 reviews existing system level solutions for healthcare in transportations and compares them with Health Drive. Section 7 concludes the paper with remarks on the prospects of Health Drive for future mobile healthcare applications in transportations.

2. Background

In many parts of the world, a large number of people in urban areas spend hours on their daily commute to and from work, traveling along the same routes at about the same time. Their travel patterns are highly predicable and regular. Consequently, there is an opportunity to form recurring virtual mobile communication networks and communities between these travelers or their vehicles, i.e., vehicular social networks (VSNs) [10]. VSNs provide an ideal platform to efficiently aggregate health information and travel information to detect traffic accidents and provide situational awareness services to first responders [11].

VSN systems are built on top of vehicular networks that provide connectivity between users and devices participating in the VSN as well as the Internet at-large. While cellular networks can provide such connectivity, the cost may be too high and the latency too large. Instead, a vehicular ad-hoc network (VANET) may be inexpensively established to connect the users and devices onboard vehicles that are physically close to each other [12]. In our paper, we leverage advantages of both VANETs and cloud computing via Internet to construct the M-VSN architecture for Health Drive, so as to provide a multi-dimensional and seamless solution for the deployment of different customized mobile healthcare applications in vehicular networks to promote safe driving.

3. M-VSN architecture of Health Drive

As shown in Figure 1, the M-VSN architecture of Health Drive consists of three tiers: network tier, mobile device tier, and cloud tier.

Network tier: As introduced in Section 2, the network tier makes use of any available connectivity upon VANETs and Internet, such as WiFi direct between the mobile devices on board vehicle, Dedicated Short Range Communications (DSRC) between the devices embedded in vehicle and roadside infrastructures, and 3G/HSPDA/LTE for connecting to the Internet. One of the crucial challenges for mobile healthcare applications is how to disseminate and collect the related sensing data efficiently and reliably over the heterogeneous vehicular networks. We will discuss the details later in Section 3.1.

Mobile device tier: The mobile device tier works on top of the network tier, to store and interpret the streaming healthcare sensing data (i.e., from wearable sensors, mobile devices, and sensors on board vehicles) and dynamic traffic data collected from the network tier. This tier is built on the S-Aframe [14] and mobile SOA framework [15] developed in our former works according to the specifications and methodologies of RESTful Web Services [16]. As shown in Figure 1, the built-in healthcare application services that support functions at the M-VSN design time could be deployed in the service layer, while the user-defined application services could be deployed at run-time to support new applications via the cloud tier. Also, we design two novel services in this tier to achieve real-time data storage and interpretation on the mobile devices: sensing data storage service and distributed knowledge reasoning service, which will be introduced in Section 3.2.

Cloud tier: The cloud tier works in parallel with the mobile device tier. The cloud tier could be built based on the Vita cloud platform [17] introduced in our

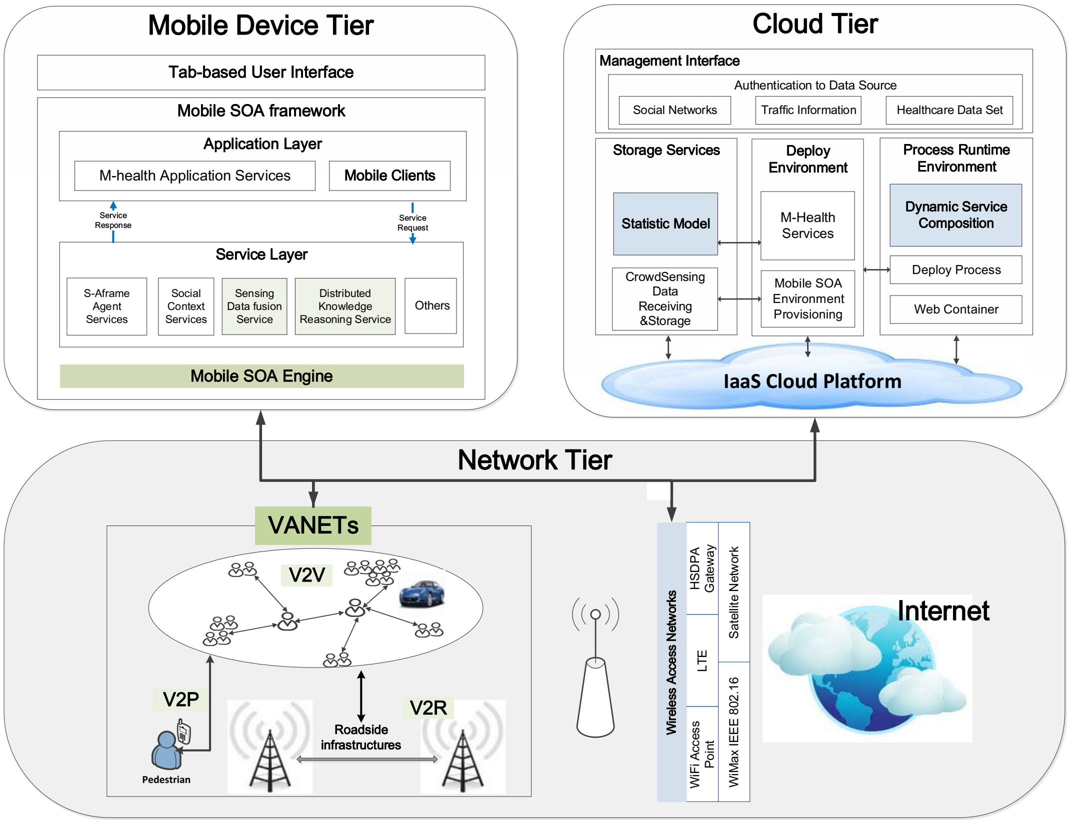

Figure 1. M-VSN architecture of Health Drive

earlier work, which is also based on the RESTful web service architecture. The applications services in the mobile tier and the cloud tier can be independent to support different healthcare applications. For applications using both mobile tier and cloud tier, the two types of application services (built in and user-defined) can be co-designed. Also, the cloud tier works as a central coordinating platform to: i) aggregate the healthcare sensing data (i.e., the real-time mood and medical conditions of the drivers), traffic data (i.e., road traffic monitoring through crowdsensing [18]), and Internet services (i.e., weather and geographic information, social activities) from multiple sources; ii) interpret the data, and composite and deliver the personalized m-health services to different vehicle users dynamically. One of the aims of the cloud tier is to extract and provide contextual information in heterogeneous healthcare environments.

3.1. Network tier

The network tier of M-VSN connects heterogeneous smart devices, including wireless sensors, mobile devices, vehicles, and roadside objects to the Internet, which enables real-time data collection in a worldwide network. It is powerful to leverage various forms of wireless technology to build an Internet of interconnected vehicles and roadside infrastructures to collect sensing data from the drivers, vehicles, and roadside units. Instead of connecting the vehicles directly to the Internet, exploring different kind of wireless communication patterns and technology can effectively decrease the message delay and communication overhead. For example, direct wireless communication between nearby vehicles does not require the message to go through the network core of the Internet, which can significantly reduce the communication delay. It also avoids unnecessary forwarding of messages through the routers in the network core when short-range wireless communication is available.

3.1.1. Communication patterns and standards

In vehicular networks, it is critical to support real-time communication to meet the application needs and provide quick responses on emergency events. For example, a vehicle that witnesses a traffic accident can quickly spread the alert message to its surrounding vehicles, so that vehicles behind can slow down in time and avoid chain-accidents. Thus, in the network tier, we propose a heterogeneous network infrastructure to support real-time data streaming. We explore different kinds of communication patterns to enable real-time communications between vehicles and other objects in the network infrastructure.

V2P (Vehicle-to-Personal device) communication supports communication between personal body sensors and the vehicles. It supports the collection of healthcare data from the drivers and gives real-time signals to the vehicles in emergency situation for proficient and safe operation. V2P communication is considered to be reliable with low data delay and data loss rate, given that the body sensors are located inside the vehicles. This communication is usually supported by short-range communication such as Bluetooth or WiFi inside the vehicle, so that the communication channel is relatively stable.

V2V (Vehicle-to-Vehicle) communication supports real-time communication and dynamic wireless exchange of data between nearby vehicles that offers the opportunity for significant safety improvement. It enables a vehicle to sense threats and hazards, calculate risk, issue driver warnings, or take pre-emptive actions to avoid and mitigate crashes. DSRC technologies have been suggested for active safety for both V2V and V2R applications. V2V communication is limited to vehicles in each other's vicinity and constrained by the moving speed and the contact time of the vehicles.

V2R (Vehicle-to-Roadside unit) communication is similar to V2V communication, which is commonly supported by DSRC technologies. It is relatively more stable than V2V communication, though it is still limited by the moving speed and the contact time between vehicles and the roadside units.

V2C (Vehicle-to-Cloud) communication enables data exchanges between the vehicles and the cloud servers. It is important for passing global geographic data to drivers and vehicles from the Internet. Since cloud computing has long been recognized as a paradigm for large-scale data storage and processing, the combination of cloud computing and VSNs enables ubiquitous sensing services and real-time data streaming, which are expected to stimulate innovations for healthcare and intelligent transportation applications. Moreover, cloud-based real-time data processing can improve data quality and assist decision-making. V2C communication is usually supported by 3G/LTE, WiFi, or WiMax technologies.

3.1.2. Real-time communication and QoS

Collecting massive data requires reliable communication with heterogeneous devices in vehicular networks. Thus, the M-VSN network infrastructure supports real-time communication based on the QoS requirements of different kinds of services. The integration of V2P communications for healthcare, V2V and V2R communications for real-time traffic data, and V2C communications for cloud-based data streaming and processing enables smart mobility and advanced services for safe driving. The above communication patterns have different characteristics in terms of reliability, delay, and cloud support. Reliability considers whether the communication channel can deliver the messages to the destination successfully without data loss or corruption). Delay concerns about the time taken for delivering the messages. Cloud support is essential for services that require the aggregation of global geographic data from different online sources or multiple entities.

Table 1 shows the reliability, delay and cloud support of the four communication patterns. V2P provides reliable communication with low delay. On the other hand, V2V and V2R communications are less reliable, since they are opportunistic and based on the availability of the vehicles and the roadside units. Their communication delay is low due to short-range communication, but the communication time is short and subjected to packet loss. All the V2P, V2V, and V2R communication patterns can be carried out without the support of the cloud. It means that no data processing by the cloud is provided by default. In contrast, V2C communication always involves the cloud servers, which support data streaming and processing. Although V2C communication is relatively reliable, its delay is high due to network traffic through the Internet.

Table 1. Communication patterns and characteristics

Communication pattern	Reliability	Delay	Cloud support
V2P	High	Low	No
V2V	Low	Low	No
V2R	Low	Low	No
V2C	High	High	Yes

Different types of m-health services could be supported by suitable communication patterns according to the QoS requirement and the necessity of cloud support. For example, healthcare services may raise alerts to the drivers and vehicles for safety awareness. This kind of applications needs real-time support (low delay) and high priority in data transmission. Cloud support is optional for reducing the data delay. Similarly, it is preferably to report traffic accident information in real-time with high priority. V2V communication is ideal for spreading local traffic information to surrounding vehicles with short delay. Cloud support is optional for data dissemination in small area, though cloud-based services could be implemented for data processing and data streaming to vehicles in larger area. On the other hand, global geographical data such as map and weather data have to be collected from different online sources and be processed by the cloud servers potentially. Thus, cloud support will be needed for data aggregation. Nevertheless, the QoS requirement of global geographical data is relatively low as the data change slowly.

3.2. Mobile device tier

The mobile device tier not only supports the flexible deployment of different web services based mobile healthcare applications, but also performs local storage and computation. Different from traditional mobile healthcare solutions [3, 4, 19] which mainly use the mobile devices as data mules and finish the computing tasks by the backside servers, in Health Drive we design the novel sensing data storage service (SDSS), and distributed knowledge reasoning service (DKRS). These services enable the mobile device to store and interpret the healthcare sensing data and traffic data dynamically with the cloud platform, so as to achieve better efficiency in real-time data interpretation for meeting the time-sensitive requirements of vehicular safety applications.

3.2.1. Sensing data storage service

As a significant amount of vehicular data will be collected during driving by the mobile healthcare applications deployed on Health Drive, a local storage medium is needed to store such data. Also, due to the number of different tabs and activities within such applications, the storage medium also needs to be accessible throughout the entire application. Considering the capacity of mobile devices, we design SDSS. SDSS adopts a SQLite database for the data storage of mobile healthcare applications and enables developers to perform database and Google Maps-oriented interactions efficiently.

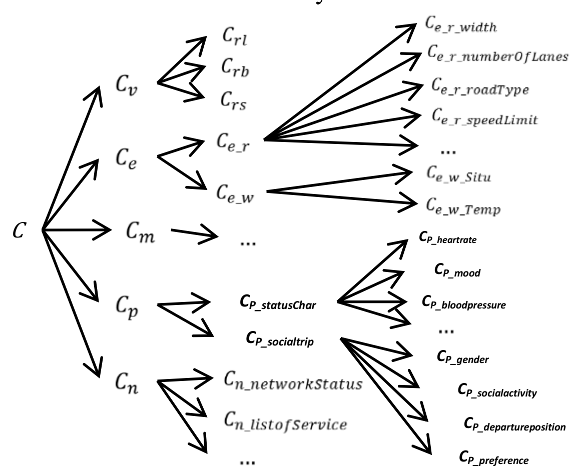

Figure 2. Sensing data table - *C*

To create and manage a local database, we implement our own version of a *SQLiteOpenHelper* object. The *onCreate* function of the *SQLiteOpenHelper* class must be overridden in order to include the SQL query that is needed to create the database. There exist various kinds of sensing data originating from multiple information sources for each mobile device on the VSNs, such as wearable health sensors, vehicular onboard diagnostic (OBD) data. It is hard to enumerate all the sensing data completely, but it is feasible to classify the core data into several main categories based on their key elements: vehicle (*Cv*), environment (*Ce*), person-being (*Cp*), mobile device (*Cm*) and network (*Cn*). Thus, the core sensing data *C* can be defined as a set *C = {Cv, Ce, Cp, Cm, Cn}*, which can be constructed in the shape of an information tree, as shown in Figure 2.

In SDSS, we adopt two main tables for storing the collected sensing data: the *C table* and the *Details table*. The primary function of the *C table* is to store the raw data collected from multiple sources upon network tier of M-VSN, and the *Detail table* describes each corresponding concept in *C table*. For instance, for a code snippets to create a new instance of the *ContentValues* variable in order to insert or update values of the database. Sets of values can be stored in *ContentValues*. The insert function of the *SQLiteDatabase* class is then called, processing the contents of the *ContentValues* variable and inserting or updating the processed values into the application's local database. Moreover, whenever a database access is required, an instance of the *DatabaseHelper* object is created first. Using the functions of the *DatabaseHelper* object, the data entries of the database can be added, modified, or removed.

3.2.2. Distributed knowledge reasoning service

In the open and dynamically changing environments of vehicular networks, it is challenging for the key-word based matching traditionally used in mobile computing to interpret the integrated sensing data (i.e., traffic and healthcare) and infer the degree of safe driving. For example, the semantics of health status of individuals may be different even when they have the same descriptions but in different contexts (e.g., a driver with the same heart rate and blood pressure, he may react fast enough in a specific range of speed and road conditions, while not in other road conditions). Also, while biomedical ontologies provide a promising approach to interpret the integrated and heterogeneous data by providing common vocabulary [20], no single ontology is sufficient and multiple ontologies must be combined in practice to achieve meaningful interpretation of sensing data [21]. Thus, in DKRS, we adopt a lightweight and scalable similarity computing method which can make use of different ontologies to calculate the similarities between two profiles. One profile consists of the concepts of safe driving which could be predefined by the developers when they deploy each specific mobile healthcare applications on Health Drive, and another profile consists of real-time sensing data of each driver when they are driving. DKRS dynamically calculates both the *semantic similarity* and *context similarity* between these two profiles, and once their similarities are lower than the threshold, it will inform the drivers and/or the backside traffic managers.

In DKRS, the *semantic similarity* of two concepts (words) is mainly decided by the impact of the following three aspects: the distance between two words; the depth of two words and the depth of their most specific common parent; and whether the direction of the path between the two words is changed.

$$Sim_{se}(I_1, I_2) = 2c^{(k+p+d)}\, depth_{common\_ancestor} \Big/ (depth_{I_1} + depth_{I_2}) \quad (1)$$

where *common_ancestor* is the most specific common parent item; *depth* represents the depth of an item in the ontology; *k* defines the length difference of the two paths between the most specific common parent item and the two items; *p* defines the path length between two items; *d* defines the changes of the directions over the path; and *c* is a constant between 0 and 1. Functionalities realizing values for these parameters are built on top of the main inference services such as consistency checking, entailment, and subsumption. For example, the concept subsumption inference service is iteratively called in the function of finding the depth of an item. That is, ontological reasoning is used for creating semantic similarity in DKRS. We can see that the range for the *semantic similarity* is [0, 1]. For example, when two items are irrelevant, there is no common parent, then *depth* (*common_ancestor*) is 0 and thus their similarity is 0. When two items are identical or synonym, we have $k=p=d=0$ and $depth_{common\_ancestor} = depth_{I_1} = depth_{I_2}$, thus the *semantic similarity* is 1.

Each concept in an ontology usually has some other descriptive objects, such as properties and related concepts, their interpretation of the concept plays an important role in the context of each concept. Thus, *context similarity* should be included in evaluating similarity. The *context similarity* is given as:

$$Sim_{co}(I_1, I_2) = \sum_{i \in [1, n_1 - 1]} \max_{j \in [1, n_2 - 1]} (Sim_{se}(I_{1i}, I_{2j})) \cdot weight_{xi} \Big/ (n_1 - 1) \quad (2)$$

where n_1-1 is the number of items as the context for the key concept in profile P_1 and n_2-1 is the number of context items in profile P_2. Note that the maximum function is employed for the reason that only the most similar pair of items is highly relevant in reality and can significantly reduce the space and time complexity in similarity computation.

Then the overall similarity integrates the *semantic similarity* and the *context similarity* as:

$$Sim(P_1, P_2) = Sim_{se}(I_1, I_2) \cdot weight_{se} + Sim_{co}(I_1, I_2) \cdot weight_{co} \quad (3)$$

where $weight_{co}$ is the weight for the *context similarity*, $weight_{se}$ is the weight for the *semantic similarity* and $weight_{co} + weight_{se} = 1$. The real value of these two weights can be dynamically switched accordingly to different specific scenarios of healthcare in vehicular safe applications, e.g., the computation capacity of mobile devices, the computation-communication tradeoff between mobile devices and cloud platform. In fact, *semantic similarity* represents similarity in a shallow level and *context similarity* represents similarity in depth. In particular, if only the shallow match is needed, $weight_{se} = 1$; if only the deep match is needed, $weight_{co} = 1$.

For the implementation of DKRS, ontology-based conceptual graphs that can be easily described in various formats, such as RDF [22] and OWL [23]. Although in M-VSN, it assumes that domain experts or mobile healthcare application developers design and provide such ontologies, they can turn to numerous existing ontologies, such as openGALEN [24]. Our current implementation of semantic and context interpretation procedure employs RDF for ontology representation and Jena2 [25] is integrated for parsing RDF. In addition, as discussed above, both the mobile device tier and the cloud tier are built on the RESTful web service. Depending on the size of the ontologies used in each application, we can design specific schemes to enable dynamic switching between mobile device and cloud platform to perform the ontologies based data interpretation, so as to achieve better time efficiency.

3.3. Cloud tier

The cloud tier works as a central coordinating platform to aggregate data from multiple sources and interpret those data, to deliver personalized healthcare services to drivers for safe driving.

In a typical mobile healthcare platform, the contextual data uploaded from multiple sources, including healthcare sensing data (from healthcare mobile sensors), traffic data (from traffic monitoring sensors), and other open data (from Internet services, like weather and geographic services). Data from those independent sources often have disparate assumptions of interpretation. The key challenge is that in most cases the assumptions would be implicit and not specified in a way that the data could be automatically

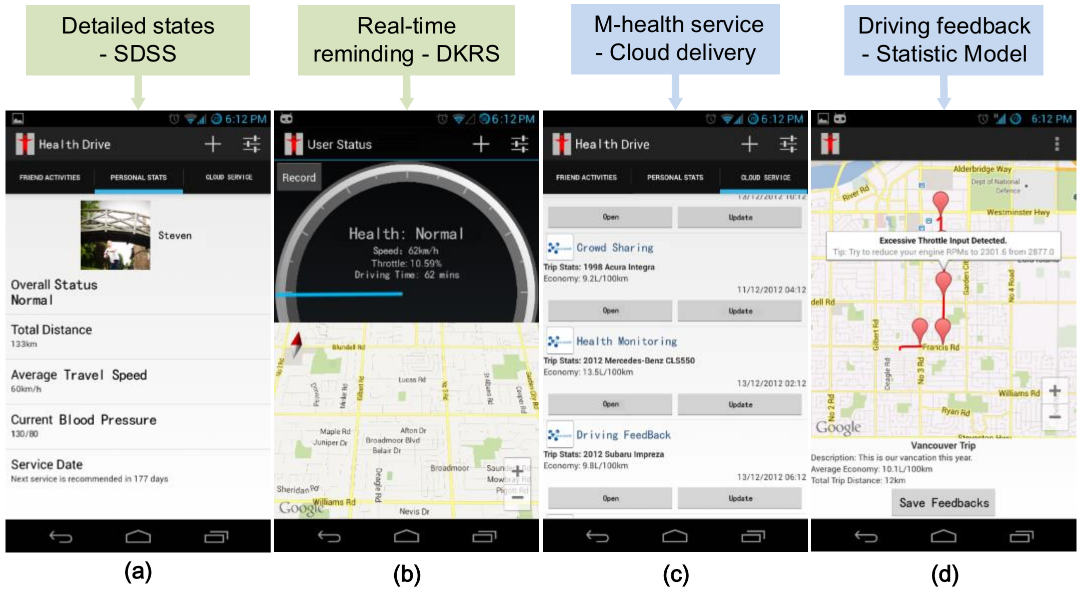

Figure 3. Screen-shots of the mobile healthcare application deployed on Health Drive

interpreted. Let us take a simple example of the unit of speed. Data about driving speed collected from a mobile device in the US is implicitly assumed to be in the unit of miles per hour. But when the same concept of data comes from Europe, it assumes the unit is kilometers per hour. In many cases sensors would just report the data as a numeric form without explicitly specifying the units. Such implicit assumptions of data interpretation have to be addressed before the services can be dynamically composed and analyzed. To deliver appropriate m-health services to drivers, we need to make the raw data from different sources context-aware, and thus the implicit assumptions of data interpretation need to be explicitly specified and registered to the cloud tier. One possible way is to require service providers to pre-specify the context definition for their mobile devices and register them to the cloud [18]. For instance, service providers can indicate the context of the mobile devices based on the locations, e.g., US or Europe. Accordingly, the data can be interpreted contextually according to the source location. By doing so, the cloud can understand and interpret the data, facilitating the dynamic composition and delivery of personalized m-health services to different drivers.

The cloud tier contains a lightweight ontology serving as the common vocabulary for the aggregation of contextual data from different sources. The unique feature of the lightweight ontology is the addition of modifiers. As introduced in our prior work [26], a modifier is used to capture additional information that affects the interpretations of generic concepts. A generic concept (e.g., driving speed) in the ontology can have multiple modifiers, each of which indicates an orthogonal dimension of the variations in the data interpretation. In a certain context each modifier is assigned by a specific modifier value. For example, the concept of driving speed can have a modifier called *distance*. The value assigned to the modifier of distance can be *ML* when the data of driving speed is annotated with US-related context, while the value can be *KM* when it is annotated with the European context. Therefore, when the cloud knows where the data come from (e.g., the location of the mobile services), the cloud can understand the context of the data of driving speed and know how to interpret and analyze the data based on the values of the modifiers associated with the corresponding contexts.

Given the lightweight ontology with the augmented contexts, the cloud can automatically process the context information and convert the data by using the context of the mobile devices. To fulfill the data conversion, the cloud can select the appropriate conversion rules from a pre-specified conversion library based on the contexts of the source and receiver [25].

In addition, the cloud tier also provides a module of data analysis and virtualization for driving statistics. After collecting and aggregating data from healthcare mobile sensors, real traffic monitoring sensors and other services, the cloud tier communicates with the data storage about the users' historical behaviors and computes certain statistics.

4. Application example

Based on the proposed Health Drive, we develop and deploy a prototype mobile healthcare application to demonstrate the functionalities of context-aware services provided by Health Drive for safe driving applications. Also, considering that the m-health service of Health Drive deployed on mobile devices are intended to run in the vehicular environments, and the healthcare application needs to be autonomous and minimize the operations of drivers, we adopt a simple tab-based interface that can be observed and controlled by the drivers. As shown in Figure 3, the user interfaces (UIs) of this mobile application mainly consists of three fragments: (i) Friend Activities, (ii) Personal Status, and (iii) Cloud Service.

As shown in Figure 3(a) and Figure 3(b), supported by the backside communication schemes, SDSS and DKRS introduced in Section 3.1 and Section 3.2, the mobile devices on board vehicles can perform the local storage and computation for safe driving in real-time. For example, Figure 3(a) shows the detailed driving and health information of drivers after driving in a short period. The drivers can check the information when they are available. Figure 3(b) shows the simply driving and health information of drivers, once their safe degree (i.e., continues driving time is too long and blood pressure becomes high, while driving speed is higher than normal) is lower than the threshold, the mobile devices will automatically alert the drivers to take an action, such as stop driving immediately and take a rest.

At the same time, leveraging the advantages of cloud computing, the module of dynamic service composition can extract and aggregate health-related and driving data from multiple sources (see details in Section 3.3). The customized m-health services uploaded by developers with driving feedbacks can be automatically delivered to the drivers' mobile devices. For instance, Figure 3(c) shows the extended crowd sharing service, health monitoring service and driving feedback service. The module of data analysis and virtualization also computes some statistics and produces the driving feedbacks based on the estimation of the driver's behaviors; as shown in Figure 3(d), the driver is suggested to decrease the throttle input when driving near Francis Road.

5. Evaluation results

We evaluate the system performances of Health Drive in terms of two parameters: time efficiency and networking overhead of mobile devices on board vehicles when finishing the interpretation of collected sensing data, as these parameters are of particular concern for safe driving vehicular applications in the real-world. The communications between the cloud tier and the mobile device tier of Health Drive use the standard web service format based on the HTTP protocol and XML data format, and the experimental environment is: ***Hardware:*** Amazon EC2 M1 Medium Instance; 3.75 GB memory; 2 EC2 Compute Unit; 410 GB instance storage; 32-bit or 64-bit platform; I/O Performance: Moderate; EBS-Optimized Available: No. ***Software:*** operating system: Ubuntu 14.04; Servers: Apache Tomcat 8.08; BPEL engine: Apache ODE1.3.4. ***Experimental devices***: Vehicle - 2005 Toyota Sienna; ELM327 Bluetooth OBD-II Module; Polar H7 heart rate sensor; and Smartphone – Google Nexus 4 (Android 4.4.2 version).

Two Nexus 4 (with LTE module) were used in driving 2005 Toyota Sienna for testing. Each test last 30 minutes, and total of 5 tests were run, and the average results were calculated. We adopt the ℰ£-GALEN ontology [24] as benchmark, and the computation task of data interpretation is to index and calculate the similarities of concepts on this ontology under the condition of four different size assertions (1000, 1500, 2000, 36000), from which we obtained four sets of data correspondingly. For each data set, we test the time efficiency of the task in two situations: perform the task on Nexus 4, and perform the task by uploading it to the cloud platform of Vita. The distribution of the task according to Poisson distribution with a rate of E=5/min. In addition, we record the network overhead on Nexus 4 when it uploads the task to Vita.

The experimental results are summarized in Table 2. The time delay when performing the task via cloud consists of: (i) response and communication time between the Vita cloud platform and the mobile devices; and (ii) processing time of the task. We find that the response time of the four sets of data are similar, with all averaging about 4.5s, while the process time mostly depends on the size of the data set.

Table 2. Overall System performance

Parameters	Data set 1(1000)	Data set 2(1500)	Data set 3(2000)	Data set 4(36000)
Time delay via cloud - response time+process time(msec)	Average: 4683+40=4723	Average: 4475+461=4936	Average: 4626+702=5328	Average: 4395+2483=6878
Network overhead	1.67MB/150 requests	1.69MB/152 requests	1.64MB/147 requests	1.59MB/143 requests
Time delay - local computation(msec)	Average: 2234	Average: 4736	Average: 7445	Average: 136073

From Table 2, we can see that Nexus 4 gets a better time efficiency when the size of data set is 1000 and 1500, while the cloud performs much better when the size of data set is larger than 1500. Since Health Drive supports dynamically performing the computation task across mobile device and cloud platform, thus the maximum time delay is lower than 7s even in the quite intensive computing situation when the size of data set is 36000. Also, considering that in our real-life, the recommended safety distance between vehicles is about 150m [27], and the speed difference between two vehicles travelling in the same direction normally will not exceed 60km/h (16.67m/s), which means the time distance between two vehicles is more than 9s (150/16.67). Thus, our experiments demonstrate that the ontology based approaches of Health Drive can interpret multiple sensing data in an efficient manner. Also, such results verify the feasibility of Health Drive for real-world deployment of mobile healthcare applications to achieve safety improvement in a considerable range of transportation scenarios.

6. Related works

To the best of our knowledge, there is no mobile healthcare system or architecture specifically designed for mobile applications of healthcare safety improvement in vehicular networks yet. However, the system and architecture level solutions for mobile healthcare applications proposed in MoCAsH [28] and HealthCloud [29] are similar to our work.

MoCAsH [28] is an assistive healthcare infrastructure based on a mobile cloud platform, which aims to facilitate the deployment of cloud computing features such as elasticity of resource demands and scalability of infrastructure to assist mobile healthcare applications. Different from MoCAsH, which is only based on the Internet, in the network tier of M-VSN architecture, we adopt a heterogeneous network infrastructure. This infrastructure exploits different kinds of communication patterns (V2P, V2V, V2R, and V2C) to enable massive data (i.e., healthcare data) to be collected in a more efficient and stable manner in vehicular networks.

Based on the RESTful web service, HealthCloud [29] provides a prototype implementation of a mobile healthcare information management system across a cloud computing platform and Android devices. However, similar to many mobile healthcare platforms [3, 4, 19], in the design of HealthCloud, the mobile devices only work as mobile clients and need to upload all the healthcare data to the cloud for processing, which may result in considerable time latency and may not be suitable for transportation scenarios. As discussed in Section 3.2 and the experimental results demonstrated in Section 5, in the M-VSN architecture of Health Drive, our solution supports the mobile device tier working in parallel with the cloud tier to store and interpret the healthcare data simultaneously. Thus, the vehicular safety applications deployed on Health Drive can achieve a better efficiency in real-time data reasoning for time-sensitive requirements in vehicular networks.

Moreover, security and privacy are always a concern for mobile healthcare applications and services in vehicular networks [30]. A number of solutions exist that could be adopted to address such concerns. For instance, based on e-health system, the authors in [31] proposed a novel solution that uses an authorization paradigm to define access levels for accessing different parts of personal data in vehicular networks. Although Health Drive does not currently incorporate the security and privacy mechanisms mentioned above, these different mechanisms can be adapted and integrated in Health Drive to achieve different levels of security.

7. Conclusions

In this paper, we have proposed Health Drive, a novel mobile healthcare platform which employs the M-VSN architecture to support the deployment of different context-aware mobile healthcare applications for safe driving in transportations. We have described the three tiers: network, mobile device and cloud in our architecture, and discussed how they can facilitate the deployment of mobile healthcare applications in vehicular networks. Based on these tiers, we have provided a seamless solution in a generic architectural model which can facilitate the efficient collection and interpretation of diverse sensing data in real-time over heterogeneous environments of vehicular networks, to deliver personalized healthcare service to drivers for safety improvement in transportations. In addition, we have presented a novel mobile healthcare application developed and deployed on Health Drive to demonstrate its functionalities for healthcare and safety improvement in transportation scenarios. Furthermore, experimental results have demonstrated the feasibility of Health Drive for real-world deployment.

In further evolution of Health Drive, we plan to focus on two aspects. One is to do more comprehensive and practical evaluations, such as the impact of the mobile healthcare applications deployed on Health Drive to drivers' performance under different traffic conditions. Also, as discussed in Section 6, security and privacy are always a concern of mobile healthcare applications. We plan to investigate and integrate different security schemes in Health Drive in the future.

8. Acknowledgments

This work is supported in part by the NSERC DIVA Strategic Research Network, by TELUS and other industry partners, and by STINT initial grant for international collaboration, SSF ProFuN project, and Vinnova GreenIoT project.

9. References

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