Computer Networks 145 (2018) 190–206

Contents lists available at ScienceDirect

Computer Networks

journal homepage: www.elsevier.com/locate/comnet

Contextual activity based Healthcare Internet of Things, Services, and People (HIoTSP): An architectural framework for healthcare monitoring using wearable sensors

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ARTICLE INFO

Article history:
Received 12 January 2018
Revised 1 August 2018
Accepted 4 September 2018
Available online 5 September 2018

Keywords:
Healthcare IoT
Activity recognition
Wearable sensors
Real-time systems
Data- and knowledge-driven techniques

ABSTRACT

Healthcare industry is gaining a lot of attention due to its technological advancement and the miniaturization in the form of wearable sensors. IoT-driven healthcare industry has mainly focused on the integration of sensors rather than the integration of services and people. Nonetheless, the framework for IoT-driven healthcare applications are significantly lacking. In addition, the use of semantics for ontological reasoning and the integration of mobile applications into a single framework have also been ignored in many existing studies. This work presents the implementation of Healthcare Internet of Things, Services, and People (HIoTSP) framework using wearable sensor technology. It is designed to achieve the low-cost (consumer devices), the easiness to use (interface), and the pervasiveness (wearable sensors) for healthcare monitoring along with the integration of services and agents like doctors or caregivers. The proposed framework provides the functionalities for data acquisition from wearable sensors, contextual activity recognition, automatic selection of services and applications, user interface, and value-added services such as alert generation, recommendations, and visualization. We used the publicly available dataset, PAMAP2 which is a physical activity monitoring dataset, for deriving the contextual activity. Fall and stress detection services are implemented as case studies for validating the realization of the proposed framework. Experimental analysis shows that we achieve, 87.16% accuracy for low-level contextual activities and 84.06%–86.36% for high-level contextual activities, respectively. We also achieved 91.68% and 82.93% accuracies for fall and stress detection services, respectively. The result is quite satisfactory, considering that all these services have been implemented using pervasive devices with the low-sampling rate. The real-time applicability of the proposed framework is validated by performing the response time analysis for both the services. We also provide suggestions to cope with the scalability and security issues using the HIoTSP framework and we intend to implement those suggestions in our future work.

1. Introduction

The integration of wireless communication, sensor, and information technology has opened new paradigms in the field of well-being and healthcare management. It enables the quality of life and extends the autonomous living of individuals at home. Today, embedded sensors can measure a wide range of physical parameters with the minimal complexity. This phenomenon becomes realistic due to their low power consumption and cheaper production cost. These embedded sensors can be integrated in small wearable devices like watches, pendants, and clothes. Moreover, they can also be applied to everyday objects or places, such as appliances, furniture, or the like, for automation purposes. Internet of Things (IoT) has radically changed the way the human interacts with things, i.e. sensors, objects, services, and applications. These entities provide continuous data streaming over a protracted period of time, based on its characteristics. The acquired data from these diversified set of sensors can be analyzed and used to enable a service or process an action based on the user's request [1–3]. Since IoT is not bounded to any particular field, it has been applied to a wide range of services [1,3–5].

IoT has profoundly changed the way of healthcare service delivery, and as a result, physicians recommend the use of health-

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https://doi.org/10.1016/j.comnet.2018.09.003
1389-1286/

related applications to patients [6]. Many applications are available which take input from the users about their daily routines and dietary habits [7,8] to report their health condition, but IoT driven healthcare can benefit from the automatic collection of information through internal and external sensors for detecting anomalous conditions. These sensors refer to the built-in sensors in smartphones [9] and wearable sensors like smartwatches [10]. IoT has been extensively studied for smart homes. The related services are based on the changes in sensor readings such as humidity, temperature, ambient light sensors, and so forth. The changes in the sensor measurements are used to control the home appliances and enhance the quality of living without user intervention. Researchers are still trying to assess the complete spectrum of IoT driven healthcare systems. There is a dire need for powerful tools that can acquire data from multiple sensor modalities such as psychological, physiological, and inertial data to validate the autonomous healthcare monitoring system.

Some studies have stressed on the acquisition of multimodal data [11] whereas others focus on analyzing the provenance of the acquired data [12]. Healthcare IoT based services are mainly implemented with inertial measurement units (IMUs) for activity recognition, event/process detection using object/location sensors, and physical state monitoring using physiological sensors [13,14]. Most of the works have been performed using event/process detection with object sensors and activity recognition. These works are specifically proposed for either inhouse patients, elders or people with specific disease which requires a proper setup or infrastructure to be deployed, hence, trading off with mobility and easiness of such systems. Moreover, the use of physiological sensors has not been exploited to its full potential yet in the field of healthcare driven IoT services. It is apparent that more usage of sensors results in wider scope of the health-related services. In this regard, we propose a framework which can combine multiple sensor modalities to provide the healthcare services in an accurate and an efficient way for all users. The use of wearable sensors in this framework allows the system to be location-independent or infrastructure-less system.

In general, IoT is a four-layered architecture with sensing, network/access, service and interface layer [1–5,15,16]. The sensing layer is responsible for the integration of different sensors, their connection to the physical world, and collection of data. The network/access layer provides the networking support and is responsible for the transfer of the data in wireless or wired networks. The service layer is managing and creating services as per the user's requirements. The interface layer is commonly used for presenting the analyzed data or the output of the desired services. The users or associated entities are able to interact with the IoT system using the interface layer. In general, IoT framework with specified layers is limited to some specific services but including another layer such as context recognizer can extend the scope of healthcare driven IoT and can be used for the automation of services. The important requirements for designing IoT based healthcare monitoring framework are summed up as follows [1–5,15,16]:

- Holistic solution: healthcare driven IoT can be used for physical fitness, safety, and health, as this solution encompasses everyone needs.
- Fusion of technologies: healthcare driven IoT can be integrated with a wide variety of sensors and can support multi-modal sensor platforms.
- Analytics and BigData: with recent advancement in cloud computing technology, multi-modal, multi-scale, and heterogeneous data can be easily pre-processed and analyzed in a reasonable time. This allows the applicability of real-time systems for healthcare services.
- Personalized services: analytics and big data techniques such as machine learning and recommendation systems expand the possibility for personalized healthcare treatments and services. It can also help early detection of anomalous conditions.
- Data for many time-lines: users can receive or access their past, present, and future predicted data anytime and anywhere.
- Telehealth features: the data and output from desired services can be shared with doctors in real-time. Moreover, doctors can monitor larger number of patients with the use of healthcare driven IoT systems.

In accordance with the requirements above, in this paper, we introduce the healthcare driven Internet of Things, services, and people (HIoTSP) framework in the context of wellbeing and healthcare using smartphone and wearable devices as shown in Fig. 1. HIoTSP is the interconnection of things (sensors), services (application and service triggering based on analysis) and people (caregivers or doctors) via the Internet for healthcare services [17]. This framework integrates the use of inertial, physiological, and location sensors for our context recognizer for deriving contextual activity to automate the service selection process. The sensor layer in HIoTSP is responsible for acquiring measurements from various sensor modalities. These sensor measurements are then transferred to the middleware via the access and communication layer which provide the means for interfacing. The middleware in the proposed framework is the smartphone which acts as a gateway for sending and receiving the information to and from the server layer. It can also perform some lightweight operations with the data stored in the buffer. The data received from the middleware is then accumulated in the storage of server layer. The server layer uses the data to recognize contextual activity to select the desired service(s), respectively. The data in compliant to the selected service is then passed to the service selection block for performing further analysis and decision making. This data is also used for summarizing and recording the event logs. The decision from the service selection is periodically checked by the middleware. As the decision is available, it is fetched by the middleware and immediately relayed to the notification center for alert generation and recommendations (the details of each of the blocks are provided in Section 3).

The proposed framework supports mobility as it can be used indoors as well as outdoors, low cost as it uses only wearable sensors and common devices such as smartphones, and user-friendliness as devices are unobtrusive, less complex, and easy to operate. The framework uses ontological reasoning or inference rules to select an application or service for analyzing, summarizing, and visualizing the data. The interface layer (notification center) in this framework explicitly deals with generating declarations based on the attained results. We have also implemented two health-related services i.e. fall and stress detection which are considered to be major anomalous conditions in the literature. The current implementation of the framework is geared towards research and small-scale field tests rather than towards the usage in practice with patients and caregivers. The contributions of the proposed work are summarized as follows:

- Integrated framework for healthcare driven IoT services that includes semantics (context recognizer) layer
- Combining multiple sensor modalities to automate the service selection as well as to cover wide range of health monitoring services.
- In-depth analysis for contextual activity recognition and related services such as fall and stress detection.
- Real-time implementation and validation of the proposed HIoTSP framework.

The rest of the paper is structured as follows, Section 2 highlights the existing studies and frameworks; Section 3 presents the

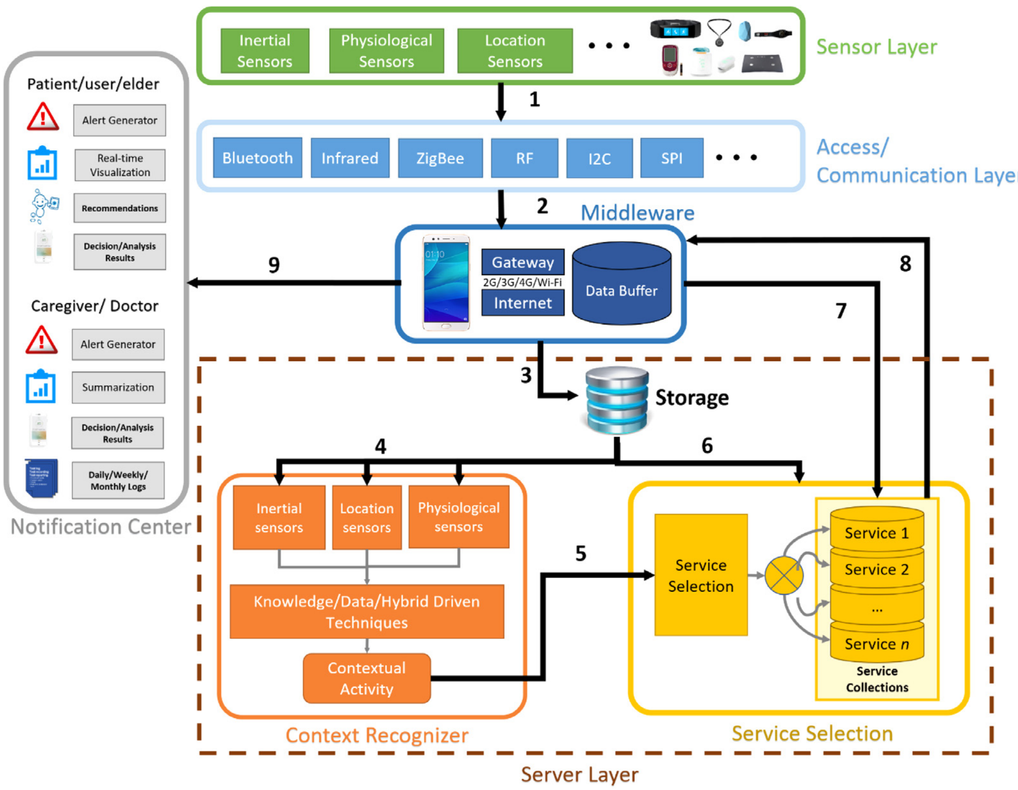

Fig. 1. The proposed HIoTSP framework.

proposed architecture of our framework. Section 4 provides the details for the implementation details of the framework and services. Section 5 explains the results from our implementation of framework modules and services. Finally, the discussion and conclusion are presented in Section 6.

2. Related works

This section carries out a literature survey of IoT driven healthcare systems. Though a lot of research works have been conducted on IoT based healthcare systems, the ones which are closely related to our scope are discussed in this section.

Niranjana and Balamurugan presented an intelligent home-based healthcare IoT system using a medical box (iMedBox) and iGate which works as a home healthcare gateway. Wearable sensors are coupled to the iMedBox via RFID link to monitor the user's health [18]. Gelogo et al. presented IoT based U-healthcare system which uses smartphone as a gateway to send health information or updates to the caregiver [19]. The system uses non-pervasive sensors like the sensors mounted on shoulder or on the chest. Istepanian et al. proposed an architecture named 6LoWPAN specifically for diabetic patients using real-time glucose sensor. It is designed to send the glucose information of the patient to the doctor or medical station [20]. Valerie and Leijdekkers presented an individual heart monitoring system for arrhythmias patients. The system was able to generate alarms and issue warnings based on the electrocardiogram (ECG) signal measurements [21]. Banos et al. proposed mHealth framework for monitoring a user's health using multiple wearable sensors. The framework emphasized more on monitoring the daily life activities rather than the physiological state of an individual. Moreover, the framework did not use semantics or integrate different applications/services to provide the summarization of health condition [22]. Khan designed a framework which focused more on the communication aspect of the health monitoring system rather than the analysis on the state of an individual [23]. Jin et al. presented a hypothetical framework for ubiquitous living environments and discussed the challenges in its compliance. The work exhibited limited details of data analysis, services, and implementation [24]. Bhatia and Sood targeted intensive care units (ICUs) for remote healthcare monitoring systems with bio-sensors and smart sensing devices. The system generated alerts based on the data abstraction level and sends it to the concerned doctors [25]. Hossain and Muhammad proposed an infrastructure for IoT healthcare services based on wearable sensors. The main idea of their system was to provide emergency response for anomalous health behavior noted from physiological sensors [26]. Yang et al. proposed an IoT healthcare system by using an intelligent box which provides network connectivity to the various sensors in home environment. The system was mainly designed to provide necessary health care services to in-home patients [27]. The works mentioned above are summarized and compared in Table 1.

It can be noticed that most of the works have focused on a specific healthcare service and users. Moreover, many of them are infrastructure-based systems which can be a hindrance to the applicability of the system in a real-life situation. Infrastructure based systems refer to the pre-determined sensor settings which lead to fixed or non-mobile systems. Most of the works focus on vital signs as the primary health care service and cannot be extended beyond this scope. The smartphone is the common device used as a middleware as it ensures the mobility. The physical activity is mostly considered for healthcare services, but it does not provide insights on the activity being performed with respect to the location and physiological signals. Contextual activity can provide the necessary insights to provide us with information as to which activity and where it is being performed. Our proposed framework introduces context recognizer layer and the integration of multiple services to provide a means of healthcare monitoring service on the go with the help of wearable sensors so that the monitoring can be performed anywhere and anytime. Since HIoTSP is a general healthcare monitoring system, it does not target any specific users. To show the applicability of the HIoTSP framework to various domains, we employed the commercial wearable devices for better realization.

3. Proposed framework

The proposed HIoTSP framework is developed for health monitoring of individuals and is shown in Fig. 1. The framework is comprised of the dependency and interconnectivity of wearable sensors with applications and services through smartphone. This framework is designed in such a way that it could support mobility, low cost, and user-friendly perspectives. Caregivers, relatives, and doctors may have the opportunity not only to monitor the current health condition of an individual but also to get insights of the behavior patterns through daily summarized logs. Details of HIoTSP framework layers and components are given in subsections below.

3.1. Sensor layer

This module is the first layer of the HIoTSP framework. The task of this layer is to collect data from various wearable sensors such as accelerometer (Acc), gyroscope (Gyr), heart rate (HR), heart rate variability (HRV), galvanic skin response (GSR), skin temperature (SKT), location sensors, orientation sensor, and many more. These sensor devices are able to infer, process, and sense health data [31]. Although other numerous sensors are available, this study focuses on the applicability of the proposed framework based on the aforementioned sensors. The Acc, Gyr and orientation can be considered as one inertial sensor but we consider them as individual sensor measurements as some of the services might not use all inertial sensors. For instance the fall detection service [32] adopted in this study uses the Acc and Gyr from smartwatch and the orientation sensor from smartphone. This is also the reason for not using preprocessing and feature extraction in the sensor layer as they may differ for the same sensor that is utilized for different services. For instance, the features using Acc measurements may vary for activity recognition and fall detection services. Similarly, the features using HR measurements may vary for activity recognition and stress detection services. The sensor layer assumes that there are n registered sensor devices, $S = \{s_i | i = 1, \dots, n\}$ and β types of sensors in each sensor device, denoted by $L = \{l_j | j = 1, \dots, \beta\}$. We constitute the following definitions from the provided notations:

Definition 1. (Sensor measurement): Let SM, sm_id_k, s, L, and K be a set of sensor measurements, unique sensor measurement id, sensor device, sensor measurement type, and number of sensor measurements, respectively. Then, a sensor measurement $sm_K \in SM$ is defined as following:

$$sm_K = \left\langle sm\_id_K,\ s_{i,K},\ l_{j,K} \right\rangle$$

3.2. Access/ communication layer

The main objective of this layer is to transfer the sensed data to the middleware, i.e. smartphone. This layer provides an abstraction to enable the proposed framework to be independent of the underlying technologies. This layer serves as a transparent interpreter for the wearable sensor data. The modularity of this layer makes the framework scalable and evolvable to future devices. The access/ communication layer includes Bluetooth, infrared, ZigBee, radio frequency (RF), inter-integrated circuits (I2C), serial peripheral interface (SPI), and so forth. The proposed framework assumes that each sensor device can communicate with the Middleware using the above-mentioned techniques and protocols.

3.3. Middleware

In the proposed framework, a smartphone acts as a middleware for all the layers and components. The data stored in the smartphone will be temporarily available in the memory and will be overwritten as the new data is acquired. The smartphone contains a trigger mechanism for sending data to a context recognizer and a service layer. It can also be used as a gateway for sending data to other hardware platforms. Since smartphone considers each sensor measurement to be independent of others, it will store each of the sensor measurement in its own buffer/queue. It is a lightweight operation as data is temporarily stored in the memory. The preprocessing of the sensor measurements is performed in the server layer which is comprised of contextual activity recognition (implicit service) and selectable services depending upon the specified application. Concurrently, the smartphone will call a function (e.g., through REST API endpoints). The function returns a value which is the decision from the selected services. The returned value is then disseminated to the notification center.

3.4. Service layer

The backend of the HIoTSP framework resides in the service layer which acquires the data from middleware, stores, processes and analyze the data, accordingly. The service layer consists of two main components: (1) Context Recognizer which is an implicit service to recognize the contextual activity for selection of desired service, (2) Service Selection along with data analytics and decision making. The details of both components are provided in the subsections.

3.4.1. Context recognizer

Context recognizer component is an essential part of our framework and deals with the semantic aspect. As the framework is designed to maintain the generality, in this regard, the context recognizer can consider knowledge-, data- or hybrid-driven approaches to define the contextual activities. The proposed framework takes into account inertial, location, and physiological sensor information to derive the contextual activities using the knowledge, data, or hybrid driven rules as proposed in [33–35]. Many works on contextual activity recognition are based on simple protocol and RDF query language (SPARQL) and web ontology language (OWL). RDF is a resource description framework and is used for conceptual description or modeling of information. Data-driven approach uses machine learning pipeline to train a model for activity recognition. A hybrid approach is a combination of data- and knowledge-driven approach for modeling contextual activity. The examples of the approaches are shown in Fig. 2.

Middleware will send the sensor data to the server layer for deriving the contextual activity using either of the approaches mentioned above. For instance, when the raw sensor readings from inertial, physiological, and location sensors with annotated activity labels are available, the data-driven approach can learn the patterns by extracting meaningful features and recognize the aforementioned activities. Similarly, the knowledge-driven approach can use ontological reasoning and domain knowledge for inferring activity labels as shown in Fig. 2b. The use of these approaches is based on the availability of the annotated data or the knowledge from the domain expert. To cope with this issue, the hybrid approach which embeds certain characteristics from both techniques can be used to overcome the problem of unavailability and uncertainty in data- and knowledge-driven approaches. For example, if the data for only physical activities such as walking, running, standing, and sitting are available, the recognized activity can be combined with other sensor modalities using knowledge-driven approach to derive contextual activity. In this study, we use

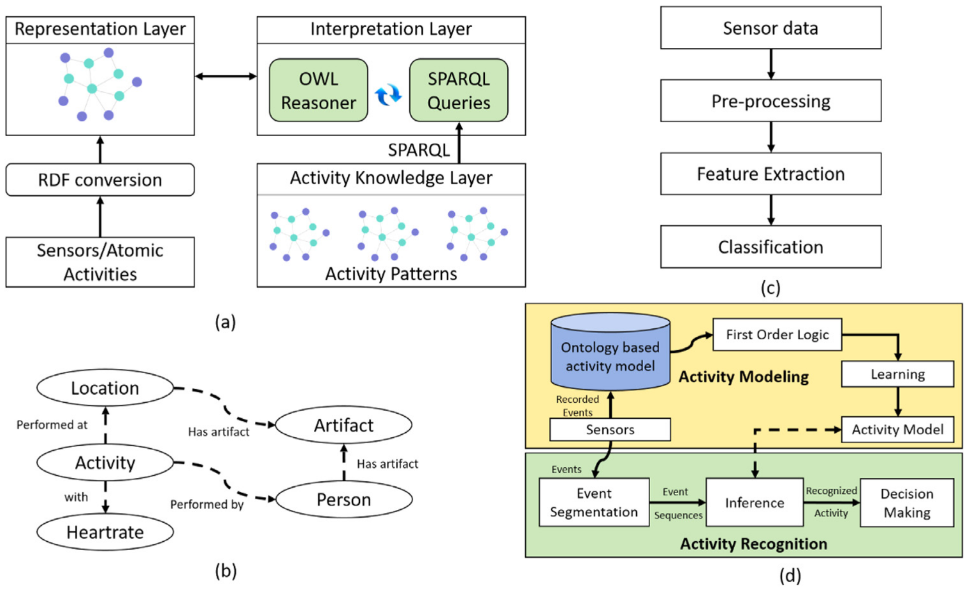

Fig. 2. (a) Knowledge-based approach for deriving contextual activity [36] (b) An example of ontological reasoning or OWL vocabulary (c) Data-driven approach for activity recognition (d) Hybrid learning based activity recognition [37].

the hybrid approach to derive the contextual activity as shown in Fig. 2(d). We first use the data-driven approach for recognizing low-level context activities based on the annotated dataset followed by the knowledge-driven approach which defines ontologies to derive high-level context activities. The details are provided in Section 4.1. The use of a context recognizer explicitly deals with deriving contextual activities to select a particular health-related service. The contextual activity is denoted as $CA = \{ca_z | z = 1, \ldots, Z\}$ where Z refers to the number of contextual activities.

3.4.2. Service layer

The data collected from the sensors via middleware will be stored temporarily for the selectable services so that it could be used for further analysis and decision making. Based on the result of the contextual activity recognition, the middleware will send the data to the cloud to select the service, and to perform processing and analysis relevant to the specified service. The service can be referred to as an application (thirty party app or self-designed app) in mobile or a decision-making service using a web server. The data sent from the middleware will also be stored in the cloud storage for summarizing and recording event logs. The service lodging process to allocate sensor measurements is defined in the following definition.

Definition 2 (Service). Let SV, sv_id_α, CA, and α be a set of services, unique service id, contextual activity, and number of services, respectively. Then, a service $sv_\alpha \epsilon SV$ in the proposed framework is defined by following:

$$sv_\alpha = \{sv\_id_\alpha,\ SM_{K,\alpha},\ CA_{Z,\alpha}\}$$

Once the service is initialized, it is necessary to check which service will be triggered in the case of same contextual activity and whether the requirement of sensor measurements is fulfilled by the available ones. The following search algorithm will be initiated for activating a service from the list of services in this layer. (Algorithm 1).

This search algorithm automates the service selection, as the service is selected based on the contextual activity, but it will get activated only if the sensor measurements are available for the specified service. For example, let us assume we have two sensor devices, a smartphone assigned sensor id “1" with Acc and Gyr and a smartwatch assigned sensor id “2" with Acc, Gyr, HRV, and GSR, respectively. For the sake of simplicity, we consider only two services in the service list, fall and stress detection. The derived contextual activity is the “desk work” which requires stress detection service to be activated. Then, we draw the following from our defined notations

$$sm_1 = \langle 1,\ 1,\ Acc\rangle,\ sm_2 = \langle 2,\ 1,\ Gyr\rangle,\ sm_3 = \langle 3,\ 2,\ Acc\rangle,$$
$$sm_4 = \langle 4,\ 2,\ Gyr\rangle,\ sm_5 = \langle 5,\ 2,\ hrv\rangle,\ sm_6 = \langle 6,\ 2,\ gsr\rangle$$
$$CA_1 = \langle house\ work\rangle$$
$$CA_2 = \langle deskwork\rangle$$
$$sv_1 = \{1,\ \langle sm_1,\ sm_2,\ sm_3,\ sm_4\rangle,\ \langle house\ work\rangle\}$$
$$sv_2 = \{2,\ \langle sm_5,\ sm_6\rangle,\ \langle deskwork\rangle\}$$

The framework will define each sensor measurement with respect to their device id and type, assuming that, fall and stress detection are assigned with *service ID* “1" and “2", respectively. The search algorithm will search for the contextual activity which is the “deskwork” and comply the availability of sensor measurements to activate the stress detection service.

3.5. Notification center

Finally, the notification center is devised in such a way that users and caregivers/doctors can monitor the performed activities as well as the result from the selected services. The notifications should be generated via smartphone based on the selected application or service for individual users, such as alert generators and recommendations. Users should also be able to visualize the sensor measurements and results from the services in soft real-time. For the caregivers, an interface should be designed in the cloud so that they can view alerts, results from the services, summarization and varying interval logs from the information acquired by the sensors.

4. Implementation using HIoTSP framework

We developed an Android application and a cloud server for the implementation of the HIoTSP framework. The application has been tested on Android operating system from version 4.3 (“Jelly Bean") to onwards. The minimum set of sensor requirements for

Algorithm 1 Service selection.

Initialize *Service Selection*
$SV = \{sv_a | a = 1, \ldots, \alpha\}$
For all the services in *SV*
  List the services, whose contextual activities match to a given contextual activity in a database
  $SVC = \{sv_b | b = 1, \ldots, \varphi\}$, *where* $\varphi \leq \alpha$, *and* $SVC \subseteq SV$
  For all the services in *SVC*
    Check the sensor measurements
    If all the required sensor measurements are available
      Activate the service

HIoTSP framework comprises location, inertial and physiological sensors. The current implementation uses Estimotes as location sensors, Microsoft Band 2 and Samsung Galaxy (Note5 and S7) for physiological and inertial sensors. The reason for choosing Estimotes and Microsoft Band 2 is their product availability and accessibility, and the provision of software development kit (SDK) to acquire the data in real-time. In our implementation, we have employed Bluetooth low energy (BLE) for Estimotes, I2C and SPI for smartphone sensors, and BLE and SDK for sensors in smartwatch. The smartphone (middleware) provides a means of communication with external sensor modalities to map the data in the required format and to abstract the mobile embedded sensors. All communications between the smartphone and the server are performed through HTTP request using a representational state transfer (REST) application program interface (API) in the server over the internet connection. The REST API has been implemented in Java server page (JSP) codes. To perform database queries and manipulations, the JSP-compliant MySQL connector library is used.

We utilize smartphone memory for buffering sensor measurements required for specific services. The smartphone then initiates an HTTP request to the REST API which performs MySQL query to store sensor data into the database. On the other hand, the smartphone checks and fetches the decision from the selected services periodically using the same protocol, i.e., REST API call through HTTP request. We have used the “Intent” class in the Android app and an API to communicate with the other apps. Our Android app is built using GraphView (an open source library for android) to show the customized graph types, multi-sensor representation and multi-plot visualization of sensor measurements. We used Amcharts Javascript (JS) library for the visualization and summarization on the cloud server. The recommendation and alert notifications were built on the standard Android APIs to trigger external applications or functionalities. The snapshots of the designed app are illustrated in Fig. 3.

4.1. Contextual activity using context recognizer

This module is of vital importance to our proposed HIoTSP framework as the selection of the services is based on the contextual activity derived using the context recognizer. It is already mentioned that any approach i.e. data-, knowledge-driven or hybrid, can be used for deriving the contextual activity. In this study, we implement a hierarchical activity recognition using the hybrid technique. As the name suggests, we use a combination of data- and knowledge-driven techniques for deriving contextual activity.

For the data-driven part, we employ PAMAP2 dataset [38] as our annotated dataset which is generated from inertial and physiological (heart rate and skin temperature) sensors. The location sensor information will be used for a knowledge-driven approach to derive the contextual activity from the annotated data. The implementation of the knowledge-driven approach is based on the ontologies defined in [33]. Both techniques will be used in a hierarchy to achieve our activity deriving task and are shown in Fig. 4. The data-driven approach follows the machine learning pipeline (see Fig. 2c) which includes pre-processing, feature extraction, and classification steps, for our annotated dataset. The context term in our study is categorized in two levels of abstraction: low- and high-level context. In our study, low-level context is the one which can be directly identified from raw-data or data-driven approach and does not require any contextual information. To be specific, locations and activities are considered as low-level contexts. High-level context requires additional information or combination of multiple low-context information to be identified. In our study, high-level context activity is derived from the combination of location and activity information. Furthermore, if a high-level contextual activity is composed of multiple activities, the data-driven approach classifies the contextual activities from the high-level ones having prior information of the location. A total of 16 activities are annotated in PAMAP2 dataset. The inferences based on the low-level contexts are shown in Table 2. The ontologies for each of the basic activities such as lying, sitting, standing, walking is defined with respect to their locations. We do not define any ontology for ascend and descent stairs as none of the contextual activity annotated in PAMAP2 dataset is compliant with the aforementioned activities.

The motivation behind hierarchical activity recognition is the bundled activities for “Home Work” and “Exercising”. Hierarchical recognition of such activities not only improves the accuracy of the recognition system but also provides meaningful insights in terms of behavior analysis. The low-level context activities are recognized using data-driven approach. In this regard, we trained 3 classification models. The first model recognizes 6 low-level context activities and infers the high-level context activities based on defined ontologies with respect to the location sensor.

The second model is applied if the high-level context activity is identified as “Home Work”. Then, the model performs the activity recognition amongst 5 activities i.e. Computer Work, Vacuum Cleaning, Ironing, Folding Laundry, and House Cleaning. The third model is applied in case of “Exercising” activity and classifies the activities such as Running, Cycling, Nordic Walking, Playing Soccer, and Rope Jumping. This method is regarded as hierarchical activity recognition in our implementation.

The attributes of PAMAP2 Dataset are described in Table 3. Each IMU measurement has been acquired at a sampling rate of 100 Hz whereas measurements from physiological sensors have been acquired at 9 Hz. As the sampling rate differs for both of the sensor modalities, there are a lot of missing values for physiological sensor measurements. A total of 54 attributes have been listed for the employed dataset. The selection of attributes with signal processing, feature extraction, and classification, are defined in the subsections.

4.1.1. Data pre-processing

Our implementation mainly comprises two sensor devices i.e. smartphone and smartwatch, and thus, we consider the sensor measurements only from two IMUs. The IMU for hand in the PAMAP2 dataset is assumed to be the smartwatch for HIoTSP framework whereas that for chest is assumed to be the smart-

Table 1
Summary and comparison of related works.

Study	Sensors[1]	Services[2]	Middleware	Location[3]	Activity[4]	Summary
Niranjana and Balamurugan [18]	RFID, BS	VSM	iMedBox	ID	✗	✗
Gelogo et al. [19]	PS, Acc	VSM	Smartphone	ID	✗	✗
Istepanian et al. [20]	Glucose Sensor	DBM	TelosB mote platform	ID	✗	✗
Gay and Leijdekkers [21]	BS, EHD, Acc	HRM	Smartphone	ID/OD	✗	✗
Banos et al. [22]	PS, IMUs	MHS	Smartphone	N.C	Phy	√
Khan [23]	RFID, PS	VSM	Base Station	ID	✗	✗
Jin et al. [24]	N.S	MHS	Conceptual Device	ID/OD	Phy / Cont	√
Bhatia and Sood [25]	OS, HR	VSM	Smart Gateway	ID	Phy	✗
Hossain and Mohammad [26]	ECG	ECGM	Smartphone	ID/OD	✗	✗
Yang et al. [27]	RFID, BS, EHD	VSM	iMedBox	ID	✗	✗
Arsand et al. [28]	PS, IMUs	DAM, DBM	Smartphone	N.C	Phy	✗
Yang et al. [29]	ECG	ECGM	Smartphone	N.C	✗	✗
Varshney [30]	PS	VSM	Intermediary device	ID/OD	Phy	✗
Proposed Work	PS, IMUs, LS	MHS	Smartphone	ID/OD	Phy / Cont	√

[1] RFID – Radio Frequency Identification, BS – BioSensors, PS – Physiological Sensors, Acc – Accelerometer, EHD – External Health Devices, IMUs – Inertial Movement Units, N.S – Not Specified, OS – Object Sensors, HR – Heart Rate, ECG – Electrocardiogram, LS – Location Sensors.
[2] VSM – Vital Signs Monitoring, DBM – Diabetes Management, HRM – Heart Rate Monitoring, MS – Multiple Health Services, ECGM – ECG Monitoring, DA – Daily Activity Monitoring.
[3] ID – Indoor, OD – Outdoor
[4] Phy – Physical, Cont – Contextual

Table 2
Defined ontologies for low-level activity and location context.

		OW	SP	HW					CM	AM	GD	EX				
				CW	VC	IR	FL	HC				RN	CY	NW	PS	RJ
Activity	Lying		■													
	Sitting	■		■		■	■		■	■						
	Standing				■	■	■	■	■	■	■					
	Walking				■			■		■	■					
	Ascend Stairs															
	Descend Stairs															
Location	Home		■	■	■	■	■	■								
	Office	■														
	Yard										■					
	Gym											■	■			■
	Mall									■						
	Outdoor											■	■	■	■	■
	Transport								■							

OW: Office Work, SP: Sleeping, HW: House Work, CM: Commuting, AM: Amusement, GD: Gardening, EX: Exercising, CW: Computer Work, VC: Vacuum Cleaning, IR: Ironing, FL: Folding Laundry, HC: House Cleaning, RN: Running, CY: Cycling, NW: Nordic Walking, PS: Playing Soccer, RJ: Rope Jumping.

Table 3
Description of attributes in PAMAP2_Dataset.

ID	Description	ID	Description
1	Time stamp(s)	25–27	3-D Acc (ms^{-2}) ± 6 g for IMU chest
2	ActivityID	28–30	3-D Gyr (rad/s) for IMU chest
3	Heart rate (beats per minute)	31–33	3-D Mag (μT) for IMU chest
4	Temperature (C) for IMU hand	34–37	4-D orientation for IMU chest
5–7	3-D Acc (ms^{-2}) ± 16 g for IMU hand	38	temperature (C) for IMU ankle
8–10	3-D Acc (ms^{-2}) ± 6 g for IMU hand	39–41	3-D Acc (ms^{-2}) ± 16 g for IMU ankle
11–13	3-D Gyr (rad/s) for IMU hand	42–44	3-D Acc (ms^{-2}) ± 6 g for IMU ankle
14–16	3-D Mag (μT) for IMU hand	45–47	3-D Gyr (rad/s) for IMU ankle
17–20	4-D orientation for IMU hand	48–50	3-D Mag (μT) for IMU ankle
21	Temperature (C) for IMU chest	51–54	4-D orientation for IMU ankle
22–24	3-D Acc (ms^{-2}) ± 16 g for IMU chest		

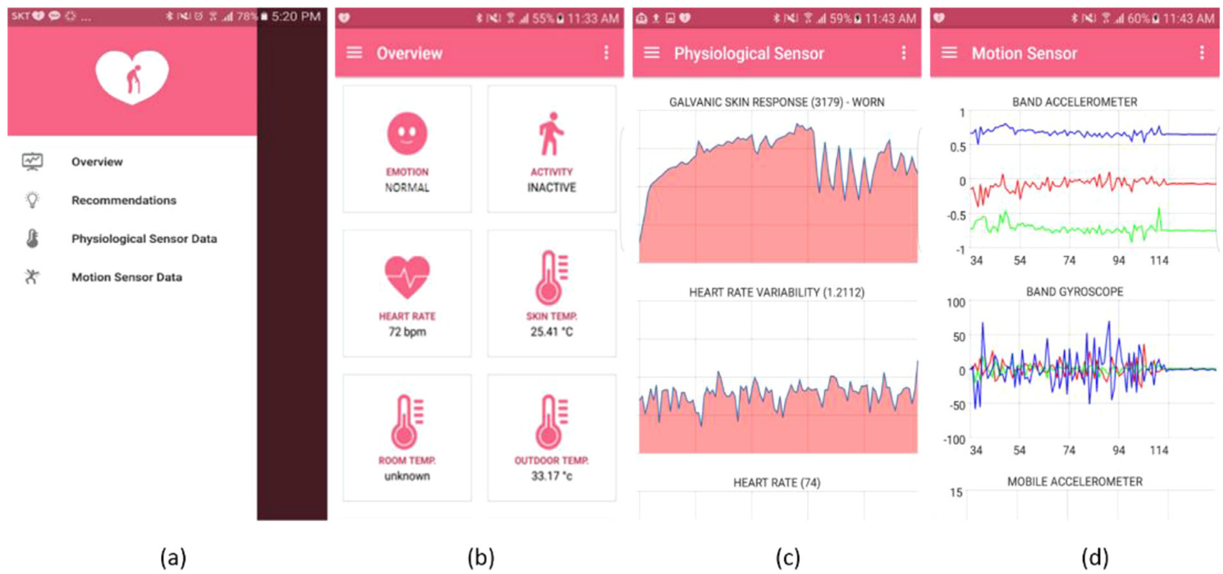

Fig. 3. Snapshots of the self-designed app for HIoTSP implementation: (a) Sliding option window, (b) Main Dashboard, (c) Real-time visualization of physiological signals, (d) Real-time visualization of inertial sensors.

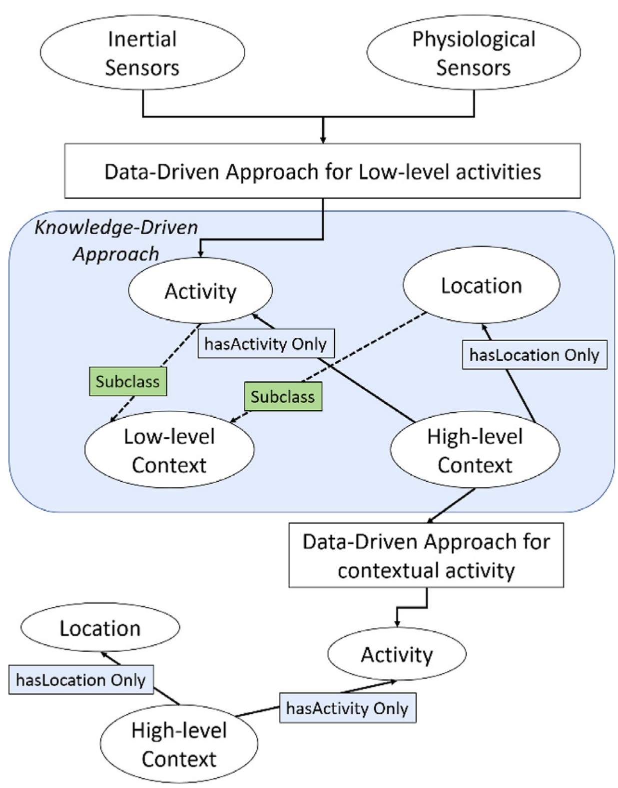

Fig. 4. Hybrid approach for deriving contextual activity: the class low-level context, its subclasses and the relationship with high-level context.

phone in the pocket. Although the performance may vary with respect to the position and placement of IMUs as suggested in [32], in this study, we only validate the applicability of HIoTSP framework with wearable sensors by taking into account the IMUs which can be substituted as pervasive sensors. We will not consider the sensor IDs which are highlighted in Table 3 as they are not compliant with our assumption for implementation. We preprocess the data as follows:

- The time stamp will be removed as we are not using the timestamp values for contextual activity recognition in the proposed framework. Moreover, these timestamp values can degrade the performance of the classifier by overfitting the decision boundary with this information.
- 90% of the heart rate and skin temperature values are missing (NaN) as the sampling rate of IMUs and physiological sensors are different in the dataset. The missing values are filled with the last available value in a specified window. This technique for filling the missing physiological sensor values is reliable as it does not tend to change as frequently as the IMU sensor measurements.
- The IMU readings from smartphone and smartwatch are acquired at 10 Hz in our implementation. Therefore, we first downsample the Acc and Gyr readings by taking the average from 10 windows for 100 samples.
- The heart rate and skin temperature sensor measurements from smartwatch are acquired at 1 Hz. We first downsample the sensor measurements by taking an average from 1 window for 9 samples.
- After pre-processing the dataset, the resultant attributes are 22 including the activity label.

The reasons for downsampling the data as mentioned are twofold. The first is to make the sampling rate compliant with the employed pervasive devices in our study i.e. (10 Hz) for inertial and (1–5 Hz) for physiological sensors. It should also be noted that most of the commercial devices as smartphones and smartwatches provide the similar range of sampling rate. The second is that the downsampling of the data has often proven to be the basis for prolonging the device's battery life at the cost of reduced recognition performance [39]. In this study, we have employed hierarchical activity classification with the hybrid technique to cope with the performance trade-off while using the downsampled data.

4.1.2. Feature extraction

We use the time windows for computing the features from IMUs and physiological sensor measurements. The window length was set to be 10 seconds for recognizing the activity. Since the IMUs and physiological sensors are distinct in nature, different features are extracted from each sensor modality. The list of the extracted features is shown in Table 4. Twelve (12) features are ex-

Table 4
List of features extracted from inertial and physiological sensors.

Sensor	Features	Description
IMU	Statistical features	Mean, Variance, Standard Deviation, Mean Absolute Deviation, Root Mean Square, Local Maxima, Local Minima, Zero Crossings, Energy, Interquartile range, First two Eigen values
Heart Rate & Skin Temperature	Structural features	The polynomials of degree one, two, and three: $f = a_0 + a_1 t$, $f = a_2 + a_3 t + a_4 t^2$ $f = a_5 + a_6 t + a_7 t^2 + a_8 t^3$
	Transient features	The trend (increasing, decreasing, or constant), the magnitude of change

tracted from each IMU sensor measurement, while 11 features are extracted from the heart rate and skin temperature sensor, respectively. A total of 250 features are extracted for each activity label in the annotated dataset.

4.1.3. Classification

We divide the number of classes as per our specified hierarchy and train the classification models. The first set consists of 6 activities whereas the other two sets comprise 5 activities each. Many studies related to physical activity classification use a single classifier for differentiating activities in the annotated dataset. A common choice for such classification algorithms includes decision trees [40], random forests [41], support vector machines [42], and artificial neural networks [43]. Some systems have also attempted to implement an ensemble of classifiers by majority voting [44], while others use a hierarchical classification approach for differentiating activities [34]. We assess the performance of different classification algorithms to select the best classifier for our implementation. We have employed 5 classification algorithms, decision trees, support vector machines, random forests, AdaBoost, and extreme learning machines (ELM) [45] for the performance evaluation. These classification algorithms have been implemented in mobile phones and cloud servers in various studies [46–49]. We use leave-one-subject-out (LOSO) analysis as our validation method suggesting that the data from one subject will be used for testing and the remaining data will be used for training. This process is repeated for p-times where p refers to the number of participants. Even though we evaluated the classification accuracy, the area under curves (AUC) and F1- scores, we only present the classification accuracy as it is mostly used evaluation parameter in activity classification.

4.2. Service implementation

Once the contextual activity is derived from the context recognizer, the smartphone automatically chooses the service based on the user/caregiver preferences. In our implementation, we have selected fall and stress detection services for assessing the applicability of the proposed framework. The activities related to movement are assigned to fall detection service. Existing studies have proved that each of these contextual activities can be a source of stress or may increase the existing stress levels such as Office Work [50], Computer Work [51], Sleeping [52], and Commuting [53]. The details of the specified services are provided in the following subsections.

4.2.1. Fall detection service

As mentioned in the former sections, sensor measurements are stored temporarily in the smartphone memory for a particular interval while the context recognizer derives the contextual activity. Those sensor measurements will be forwarded to an android application/cloud server, once the service is selected. We have employed the fall detection algorithm from our previous work [32] which proposed the fall detection method using Acc, Gyr, and pitch angles from the orientation sensor. The use of identical sensors encouraged us to implement the method in the soft real-time environment. In [32], we used 70% of the annotated data for optimization of threshold values to detect the fall but in real-life scenarios, the fall data is not available in prior. Therefore, we optimize the threshold values based on the walking activity as it can be recognized using our context recognizer and this activity is closely related to fall events [54,55]. In addition, we extended our dataset from 6 to 8 participants using our self-designed android application. The subjects participated in the experimental setup comprise four men and four women, aged from 20 to 31 years, weight from 45 to 106 Kg, and height from 155 to 172 cm, respectively. Each session recording was 2 – 3 minutes consisting of a different number of falls. A total of 10 sessions were recorded for each participant. Each of them was advised to wear a smartwatch on the dominating wrist while keeping a smartphone in the pocket. Participants simulated 4 different types of fall such as backward fall, forward fall, right lateral fall, and left lateral fall, along with low-level context activities. High cushion mattress was used for simulating the falls to avoid any injury.

4.2.2. Stress detection service

The same android app was used to collect the sensor measurements from smartwatch for HRV and GSR sensors. Data was collected from 8 subjects using international affective picture system (IAPS) [56]. The pictures are rated from negative to positive valence (1–9) and from low to high arousal (1–9) which can project the stress and non-stress pictures. Based on Russell's circumplex model [57], stress is indicated by negative valence with high levels of arousal, and thus, the pictures with the specified ratings were selected for inducing stress in the subjects. The data acquisition process is shown in Fig. 5. Sensor measurements were first normalized using min-max normalization [58]. This step was essential to perform as large variations were recorded in GSR sensor measurements amongst different subjects. The list of features extracted from the recorded data is provided in Table 5. Those are the most commonly used features in the similar studies. The computation details for the extracted features can be found in the studies [59–61]. Furthermore, we also extracted the first 10 dominant wavelet coefficients and computed their absolute and angular values as the candidate features.

Once the features are extracted from the sensor measurements, the classification model is applied for stress detection service. We employed the same classification algorithms as those of activity recognition to select the best classifier and assessed the stress detection performance using classification accuracy and F1-score, respectively.

5. Results

This section presents the results for the implicit service (contextual activity recognition), and selectable services (fall and stress detection).

5.1. Contextual activity recognition

We trained 3 classification models for low-level context activities, Home Work activities, and Exercise based activities. The sen-

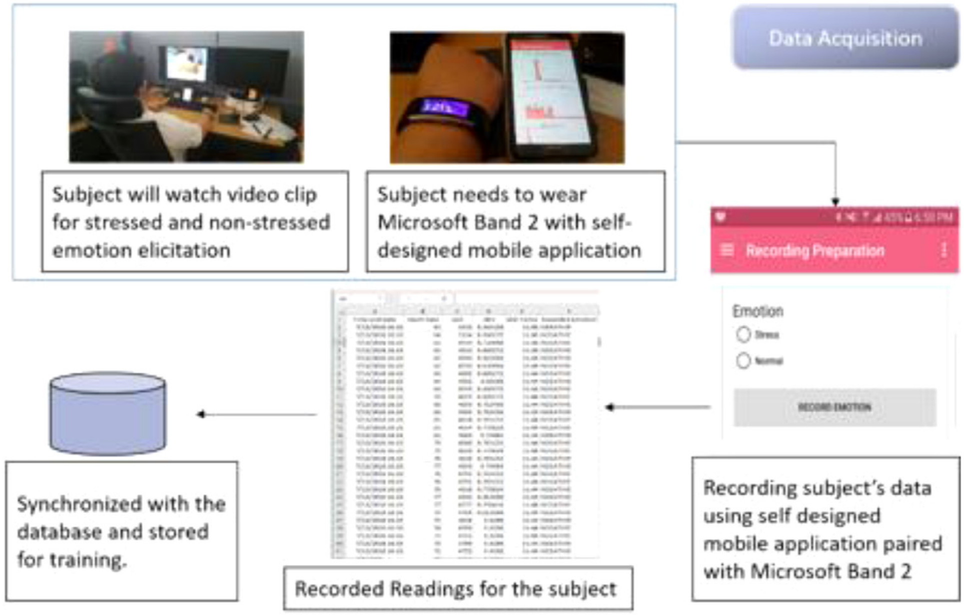

Fig. 5. Data acquisition process for stress recognition service.

Table 5
List of extracted features from HRV and GSR sensor measurements for stress detection service.

Features	List
Time domain	Mean, first difference of the mean values, second difference of the mean values, standard deviation (SD), first difference of the SD, second difference of the SD, median, covariance, interquartile range, 25th percentile, 75th percentile, skewness, kurtosis, root mean square value, min, and max
Frequency domain	Number of peaks, magnitude of the first five components, spectral peak features, spectral power features, the measures of spectral power and percentage of the sum of absolute values from high and low frequencies, normalized value of the frequencies, the relative value of each power component (HF, LF, VLF), sympathovagal balance High frequency (HF): 0.15 - 0.4 Hz Low frequency (LF): 0.04 - 0.15 Hz Very low frequency (VLF):0.0–0.04 Hz
Specific features (HRV)	SD of RR intervals (SDNN), percentage of all RR intervals which have more than 50 milliseconds of difference (pNN50), root mean square of successive differences (RMSSD), SD of the averages of RR intervals (SDANN), SD of ith RR interval (SDNNi), triangular interpolation of RR interval histogram (TINN), triangular index (TI) of HRV, spectral power and percentage of the sum of absolute values from high and low frequencies
Specific features (GSR)	Mean, SD, min, max and median values from amplitudes and frequency responses of filtered window signals passed through 4th order elliptic low pass filter at 4 Hz, signal power of the skin conductance
Nonlinear features	The scatter plot of RR values of index n in horizontal axis and RR values of index n + 1 in vertical axis, SD of long-term HRV as major axis, and SD of short-term HRV as minor axis
Time Frequency domain features	First 10 dominant wavelet coefficients from Fourier transform of the sensor measurements in a specified window length. The absolute values of the extracted wavelet coefficients, and the angular values of the extracted wavelet coefficients.

sor measurements for training and testing the classification models have been used from PAMAP2 dataset. In order to accurately classify the activities from each category, five different classification algorithms have been evaluated. The purpose is to select the model with the best accuracy for our implementation. The analysis for selecting the best classifier is conducted in MATLAB (Release 2015b) and the implementation of the classifier in a real-time system is carried out using the libraries of Weka data mining software [62]. The recordings from 9 subjects are available for the low-level context activities. The first model is trained to classify between six low-level context activities: lying, sitting, standing, walking, ascend stairs, and descend stairs. The classification results for these six activities have been consolidated in Table 6.

Table 6
Classification accuracies for low-level context activities.

Classification Method	Accuracy (%)
Decision trees	61.45
Support vector machines (RBF kernel)	67.39
Random forests	81.79
Adaptive boosting method	84.67
Extreme learning machines	87.16

The best result in terms of accuracy for the low-level context activities has been obtained using extreme learning machines (a variant of artificial neural networks). The same radial basis function (RBF) kernel was used for both support vector machines and extreme learning machines. The accuracy of each low-level context activity using extreme learning machines is displayed in the confusion matrix (see Fig. 6). The classifier shows good results for the activities such as lying, sitting, and standing, as they are intuitively distinguished activities. Similar activities like walking, ascend stairs and descend stairs have relatively lower precision than the former ones. However, the classification accuracy is over 80% for each of the activities which are considered to be a satisfactory recognition result in terms of physical activity classification works.

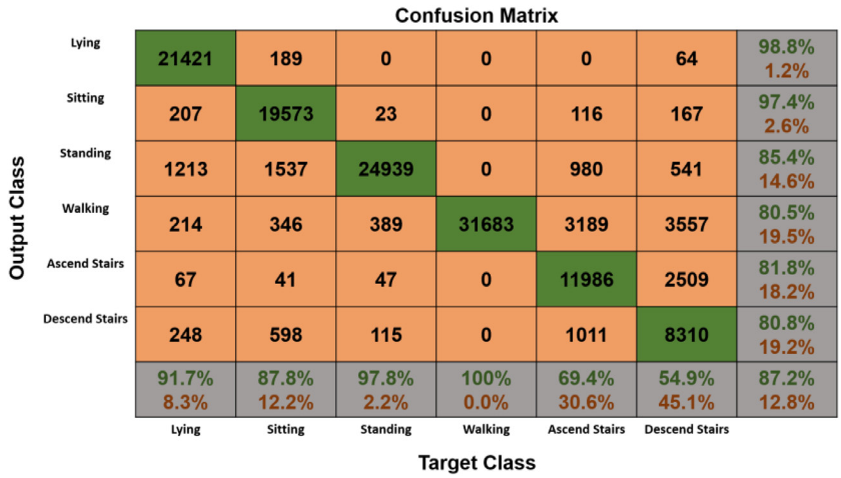

Fig. 6. Confusion matrix for recognition of low-level context activities using extreme learning machines.

Table 7
Classification accuracies for house work activities.

Classification method	Accuracy (%)
Decision trees	66.98
Support vector machines (RBF kernel)	78.42
Random forests	80.55
Adaptive boosting method	84.06
Extreme learning machines	84.60

Table 8
Classification accuracies for activities related to exercising.

Classification method	Accuracy (%)
Decision trees	67.90
Support vector machines (RBF kernel)	68.05
Random forests	76.03
Adaptive boosting method	82.58
Extreme learning machines	86.36

Table 9
Optimized thresholds for fall detection service.

Threshold	Values (unit)
α_2 (Acc)	2 (Degrees)
α_3 (Acc)	1 (Degrees)
α_2 (Gyr)	25 (Radians)
α_3 (Gyr)	2 (Radians)
α_4 (Pitch angles)	15 (degrees)

The next trained model is for the activities related to "House Work" which comprises 5 distinct activities such as computer work, folding laundry, vacuum cleaning, ironing, and house cleaning. Amongst these activities, the sensor measurements for vacuum cleaning and ironing activities are available for all the subjects. However, those for other three activities like computer work, folding laundry, and house cleaning are available only for 2, 3, and 4 subjects, respectively. We used the bootstrapping method with replacement to overcome the unbalanced measurement issue. The classification result for the "House Work" activities is presented in Table 7.

The analysis shows that the best result was again obtained using extreme learning machines. But, we analyzed the classification accuracy of each activity and observed that extreme learning machines fail to recognize the folding laundry activity. Although we want to select the best classification model in terms of accuracy, we have to select the model which can distinguish and recognize all the specified activities to our least concern. In this regard, we choose the adaptive boosting model for the "House Work" activities as it achieves considerably good accuracy and does not show the weakness exhibited by extreme learning machines for folding laundry activity. It was also observed that the adaptive boosting method achieves better precision for all the "House Work" activities compared to the extreme learning machines. The classification accuracy for each activity using adaptive boosting is shown in Fig. 7.

The last model is trained for the activities related to "Exercising" which comprises running, cycling, Nordic walking, playing soccer, and rope jumping. The sensor measurements for running, cycling, Nordic walking, and rope jumping are available for all the participants except one whereas those for playing soccer is available for 3 participants only. Similar to the "House Work" activities, we use the bootstrapping method with replacement to overcome the issue of an unbalanced number of measurements. The classification result for the "Exercising" activities has been consolidated in Table 8 and Fig. 8, respectively.

Extreme learning machines achieve the best classification result for activities related to exercising. Some samples from Nordic walking and rope jumping are misclassified as running whereas some from playing soccer are misclassified as rope jumping and vice versa. Despite these discrepancies, the classifier achieves a good result in distinguishing similar kind of activities.

It is also worth mentioning that these classification accuracies are attained by using sensor measurements from a subset of sensor devices in PAMAP2 dataset. The achieved classification results are recorded as 87.16%, 84.06%, and 86.36%, for low-level context, "House Work", and "Exercising" activities, respectively. The results prove that our implementation of context recognizer using the proposed framework performs well for activity recognition tasks and is able to classify a wide range of low-level and high-level contextual activities.

5.2. Service implementation results for fall detection service

The adopted fall detection algorithm heavily relies on the optimization of the sensor measurements for detecting the fall. In our implementation, we took 30% of the participant's data which is associated with walking activity to optimize the threshold values by comparing the results with our recognition model for low-level context activity. We used 70% of the data for testing the fall detection service in our service implementation. The optimized threshold values are shown in Table 9, where all the values are rounded up to their nearest integer values. Table 10 provides the

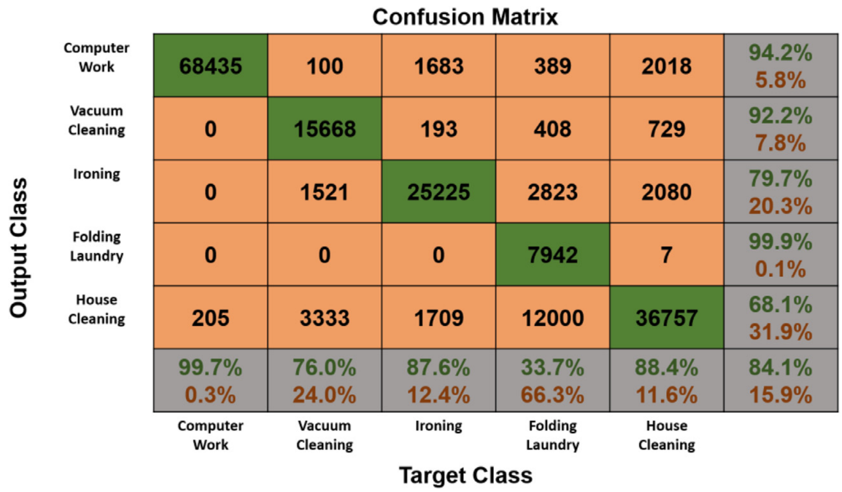

Fig. 7. Classification accuracy for each House Work activity using adaptive boosting.

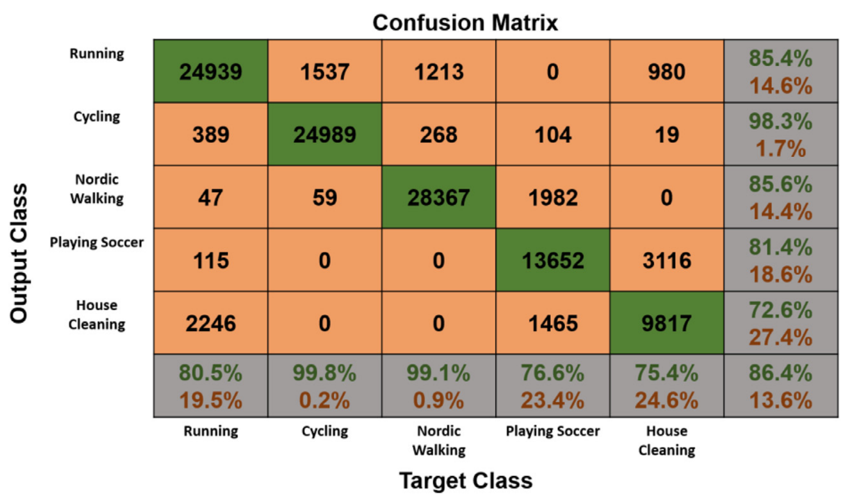

Fig. 8. Confusion matrix for exercising activities using extreme learning machines.

Table 10
Acquired results from fall detection service.

Sensor	Se	Sp	Acc (%)	ET (s)
Acc (Only)	0.9488	0.5274	83.35	0.1269
Gyr (Only)	0.8880	0.3872	79.63	0.1337
Acc + Gyr + Pitch	0.9122	0.9871	91.68	0.2157

Table 11
Analysis results for stress detection.

Method	Accuracy (%)	F1 score
Decision trees	78.83	0.8191
Support vector machines (RBF Kernel)	79.05	0.8280
Random forests	79.76	0.8370
Adaptive boosting	82.93	0.8508
Extreme learning machines	82.76	0.8492

analysis for fall detection system in terms of sensitivity (Se), specificity (Sp), accuracy (Acc), and execution time (ET). The results validate the efficiency of our method as it achieves better trade-off in terms of specificity and sensitivity with reasonable execution time. The method we adopted for fall detection service has already been compared with the existing works employing threshold based techniques in [32]. Moreover, we have implemented the services for validating the applicability of the proposed framework. The methods other than the adopted one can be used to match the resource and environmental constraints. The results in terms of receiver operating characteristics (ROC) is shown in Fig. 9. It can be visualized that the results are least distant from the reference point (0,1) which is considered to be a good indicator of the efficacy of the system.

The self-designed app generates a local alarm in the smartphone, and sends the results to the cloud server for recording the event log. An alarm is used for notification to test the working of the system, but other means of communication such as text or messages can also be applied.

5.3. Service implementation results for stress detection service

To analyze the performance of stress detection, we use LOSO analysis, suggesting that the data from 7 participants is used for training and that from the remaining 1 participant is used for testing. The detection analysis is repeated 8 times and averaged for getting the resultant classification accuracy. The stress detection result from different classification algorithms is presented in Table 11. The best result is obtained using the adaptive boosting method with the classification accuracy and F1-score of 82.93% and 0.8508, respectively. It is not justifiable to compare the obtained classification accuracy with the existing methods straight away as

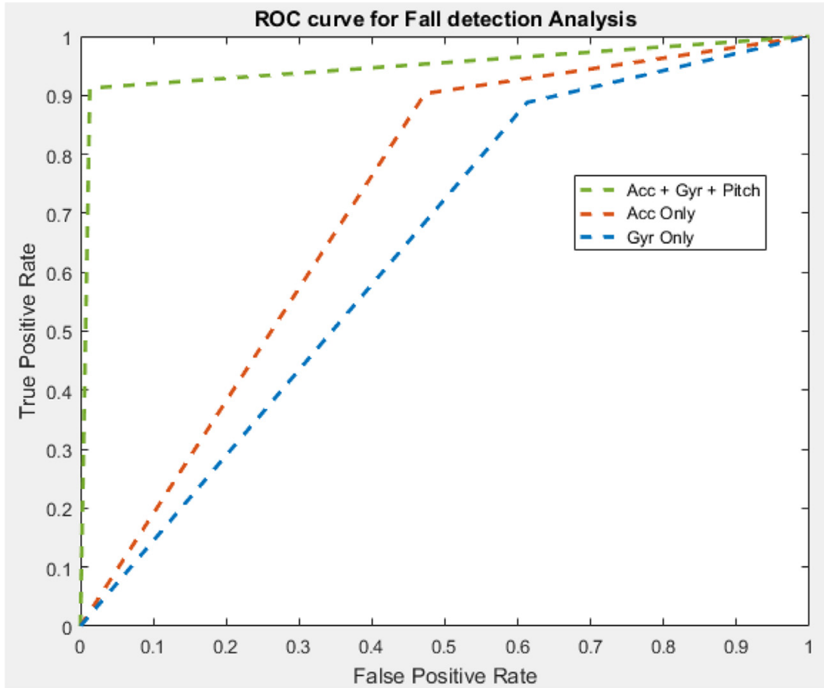

Fig. 9. ROC curve based on the fall detection service.

they differ in devices, sampling rate, acquisition protocols, and so forth. For instance, Setz et al. [63] used an electrodermal activity (EDA) sensor having the sampling rate of 16 Hz for stress recognition. Kim et al. [64] employed sensorized t-shirt with an embedded HRV sensor to recognize stress using self-reported scores. Arnrich et al. [65] used Montreal imaging stress task (MIST) to induce stress and considered GSR, Acc, and pressure sensors having 25 Hz sampling rate to record the sensor measurements for stress recognition. There are other works as well which deal with stress detection using wearable sensors with varying devices, sampling rates, and acquisition protocols. The accuracies achieved using these existing works lie in the range of 66.1% – 82.8% [52,63,65,64,66–69], respectively. Although we cannot compare our reported accuracy directly with the existing methods, we show that the achieved accuracy of 82.93% is in the similar range as achieved by the aforementioned works. Therefore, it is considered to be adequate considering the use of non-invasive wearable sensors and real-time settings.

It was also noticed that the result from extreme learning machines was very close to that of the adaptive boosting method. In this regard, we recorded the execution time from both classifiers during testing stage and found the execution time of the adaptive boosting method to be 0.9 milliseconds, which is less than that of the extreme learning machines (1.3 milliseconds). By considering the classification accuracy and the execution time, we selected the adaptive boosting model as the best classifier for stress detection service.

5.4. Response time analysis for service integration

Response time for fall detection has a significant importance and is measured by the local response time (difference between the time when subject hits the mattress and the time when fall is detected by the system) and the server update time (difference between the time when fall is detected by the system and the time when the fall data is logged in a cloud server). In our implementation, we used REST protocol for the communication between the middleware and the server. The use of different protocols such as REST, MQTT, ZeroMQ and so forth may result in different response times as highlighted in [70,71], and have different characteristics. For instance, HTTPS for securing REST may yield similar response time to the SSL/TLS layer of MQTT. The response time may increase for REST protocol when a new connection is requested, while MQTT may keep the channel open. More details regarding the difference between MQTT and REST protocols can be found in [72,73]. The protocols can be employed based on the developer preferences and environmental constraints. The analysis for the local response time and the server update time is presented in Table 12. The mean local response time for the fall detection alarm in smartphone is under 1 s. The fast response time is the result of direct computation in smartphone. However, unlike the response time, the server update time takes around 2 seconds, which is tightly correlated with the internet connection. Moreover, an Android application pushes the data to the server in every one second, which results in the reported delay.

Table 12
Response time analysis for fall detection service.

Simulation #	Local response time (s)	Server update time (s)
1	0.718	2.142
2	0.708	2.438
3	0.395	2.688
4	0.501	2.532
5	0.782	2.175
6	0.543	2.391
7	0.423	2.279
8	0.448	2.557
Mean	0.565	2.399

Similarly, for stress detection service, we evaluate the performance using transmission (the time it takes to send event details to the server) and processing delay (the time of execution on to the decision). The service was tested on Long Term Evolution (LTE) network, and the transmission delay for the sensor measurements is reported to be 1.148 seconds. The Android application pushes the data to the server for physiological signals in every 180 seconds and the processing delay to determine stress state is reported to

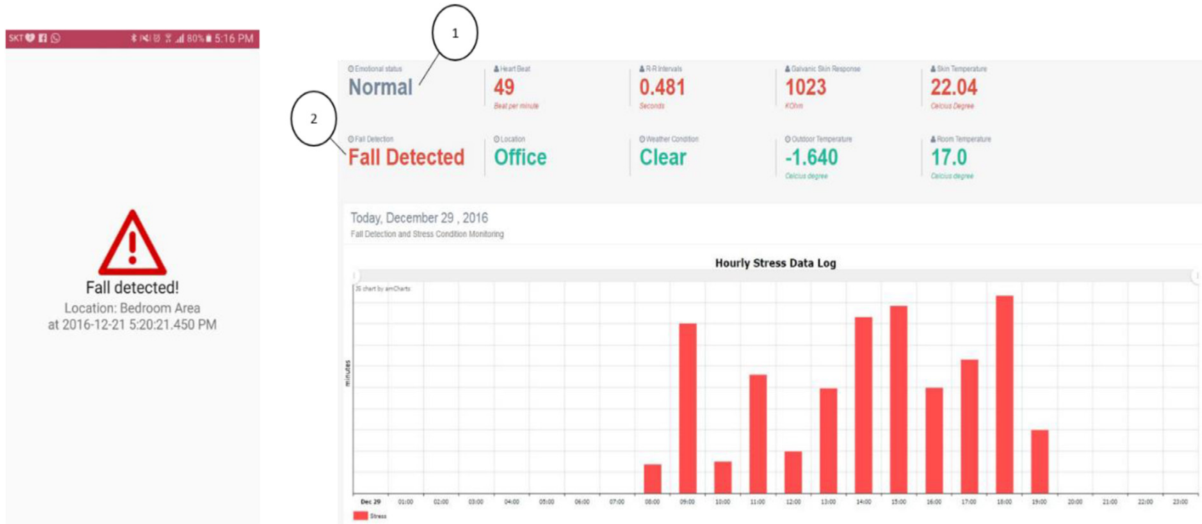

Fig. 10. Visualization results: (1) stress detection, (2) fall detection, services.

be 1.9 milliseconds (including feature extraction and classification). Fig. 10 depicts a snapshot for fall detection event in mobile along with the information on the server for stress and normal conditions.

5.5. Battery usage analysis on the active services

To show the advantages of automatic service selection proposed by our work, we performed smartphone battery usage analysis. The battery usage is the focus for the analysis since smartphone acts as the middleware and thus, will be frequently carried by the user to take benefits from the provided services. Besides, a smartphone is the only battery-powered device in our framework for which performance depends on what services are running. The analysis is performed based on four cases: when no service is activated, when both the services are running, when only fall detection service is running, and when only stress recognition is running. While recording the battery usage with running services, the user was allowed to operate the smartphone casually, such as message and email checking, lightweight web browsing, and listening to music (without heavy usage such as running 3D games and playing high definition videos). The battery percentage was recorded in every minute since the battery was in fully-charged condition. The experiment was repeated for each of the aforementioned cases.

Fig. 11 shows a snapshot of the battery usage in the first 180 minutes of recording, with respect to the four cases. The case referring to "No service" is used as a baseline for other three cases. As expected, running both services simultaneously as indicated by the second case, drains the smartphone battery almost 50% in three hours. The third case which considers only fall detection service consumes less battery as compared to the second case when both services are running. The fourth case, which uses only stress detection service consumes the least battery, since it does not require high sampling rate sensors from the smartphone, such as Acc and Gyr. The result shown in Fig. 11 justifies that we can save battery consumption through automatic service selection using HIoTSP framework.

The continuous monitoring and provision of healthcare services highlights the inherent issue of battery life which requires charging every now and then. However, this is a trade-off paid for using such kind of services. Moreover, with the advent of new technologies such as inductive or wireless charging, the burden of remembering to plug the smartphone for recharging has been reduced to

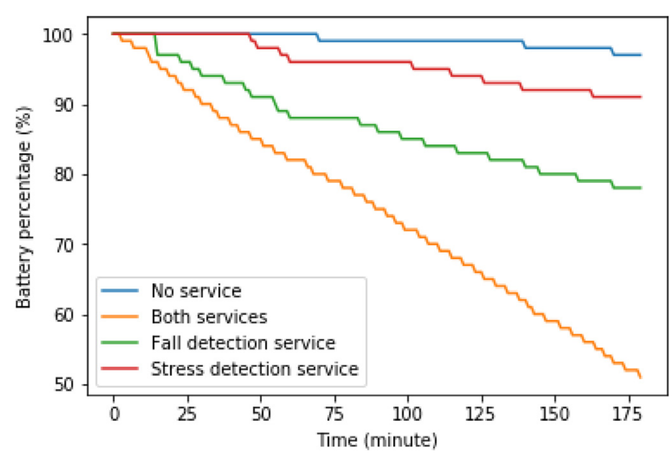

Fig. 11. Battery usage analysis.

some extent, which allows consumers to use IoT services on the go.

6. Conclusion and future works

The characteristics of healthcare provision have been transformed from clinic-centric to service-centric healthcare. This transformation has been mainly led by the increasing development in IoT technology, which provides seamless connection of cloud storage and devices to patients, individuals, healthcare services, hospitals, and so forth. In this paper, we have proposed the HIoTSP framework that is designed to collect data from wearable sensors, which not only monitors the health of an individual through a wide range of activities but also enables automated services for increasing the quality of life. One of the highlights of this framework is the automated selection of services based on the contextual activity and the use of wearable devices which are easy to use and are commercially available.

The layered architecture of HIoTSP allows the framework to perform various tasks in a synchronized manner to achieve the desired effectiveness. The framework also integrates various services and allows the interaction with other people like doctors and caregivers via its notification center. The services we chose for our implementation are also compliant with the healthcare monitoring of an individual.

This paper also presents a hierarchical approach for recognizing high-level contextual activities from only non-invasive wearable sensor devices. We conducted a series of experiments to ensure the reliability of context recognizer, as the services are triggered based on the derived contextual activity.

Two services, fall and stress detection, have been implemented and validated through experiments to prove the realization of the framework in a real-life situation. Response time analysis has also been conducted to ensure the applicability of the specified services in soft real-time space. We also provide the interface for doctors and caregivers which provides the event log and summarization of stressed events, hence, providing a way to analyze the individual's behavior in their daily lives. The desirable properties of our work are summarized as follows:

- An integrated framework (HIoTSP) is proposed for healthcare driven IoT services which has an IoT layered architecture to derive the contextual activities.
- The framework only considers wearable sensors for contextual activity recognition and health related services which provides high degree of mobility and pervasiveness.
- An automated selection of services based on the contextual activity is another highlight of our HIoTSP framework.
- Multiple agents can be involved for monitoring health state by receiving alerts or recommendations and visualizing the summarized log events.
- Two services, fall and stress detection, are implemented and validated using the proposed framework to show the applicability in real-world environments.

Although we have covered many aspects of the healthcare driven IoT framework there are still some challenges which need to be addressed. Some of them are battery issues, data management, security, and scalability. We conducted the battery analysis based on the implementation of services. It is apparent that even the use of the automated service selection can drain the smartphone battery which can create a hurdle for continuous health monitoring service. In this regard, some of the algorithms can be moved to middleware or sensor layer consisting of light weight operations rather than sending the data first to middleware via Bluetooth and then to the server via mobile communication. We assume that this would save a lot of energy since radio communication is more battery intensive compared to the simple processing. Data management is crucial as the data nowadays is increasing in terms of volume, velocity, and variety. Scalability addresses the issue of increasing number of users and devices. It is well known that personal computers and physical devices do not possess the capability of handling huge amount of data generated from wearable sensors in IoT setup. We intend to use distributed data storage services such as Apache HBase, MongoDB, and Cassandra. The data from the middleware will be sent to the Amazon simple storage via "s3cmd utility" and then will permanently be stored at the online server which stores the data in a distributed manner. Security concerns also need to be addressed in this framework such as data and network security. For the network security, we may either use lightweight anonymous authentication protocol or stacking a secure REST approach on top of the RESTful services for adding authorization in a request. The data security issue for the access via a notification center can be solved by using authentication mechanisms, such as providing user ids and passwords for the individual agents. This mechanism has also been used in several existing studies. The use of the mentioned protocols highly depends on the compliance with soft-real time system requirements and quality of services, respectively.

We are also keen to analyze the human behavior based on the context recognizer. We plan to model the process of activity patterns to analyze the individual's behavior, and this can help in personalizing the services and recommendations for each individual. Moreover, we can also analyze the relationship between a certain pool of activities with health anomalies like stress, fall, and emergency events.

Acknowledgment

This research is partially supported by Basic Science Research Program through National Research Foundation of Korea (NRF) funded by the ministry of Education (2015R1DA1A01061402) and Institute for Information and Communications Technology Promotion (IITP) grant funded by the Korea government (MSIP) (No. B0113-15-0002, Development of Self-Learning Smart Ageing Service based on Web Objects).

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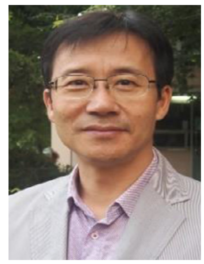

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