UbiHeld - Ubiquitous Healthcare Monitoring System for Elderly and Chronic Patients

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Abstract
Once the person's identity is established, the most important aspects of ubiquitous healthcare monitoring of elderly and chronic patients are location, activity, physiological and psychological parameters. Since smartphones have become the most pervasive computing platform today, it is only a logical extension to use the same in healthcare domain for bringing ubiquity. Besides smartphone, skeleton based activity detection and localization using depth sensor like Kinect make ubiquitous monitoring effective without compromising privacy to a large extent. Finally sensing mental condition is made possible by analysis of the subject's social network feed. This paper presents an end-to-end healthcare monitoring system code named UbiHeld (Ubiquitous Healthcare for Elderly) using the techniques mentioned above and an IoT (Internet of Things) based back-end platform.

Author Keywords
Ubiquitous Computing, Health-monitoring, mHealth, IoT, Elderly People Care

ACM Classification Keywords
H.1.2 [Information Systems]: User/Machine Systems.; C.3 [Computer Systems Organization]: Special-Purpose and Application-Based Systems;; J.3 [Life and Medical Sciences]: Medical information systems- *mHealth*

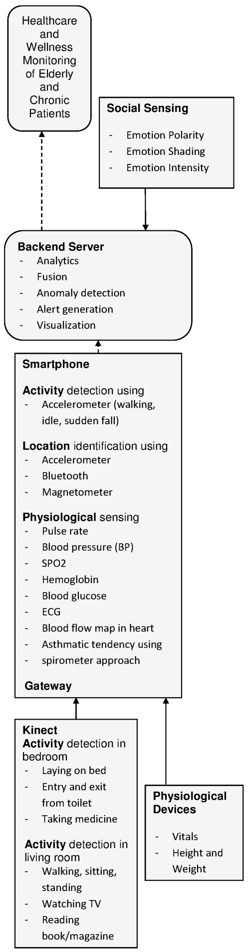


Figure 1: The Deployment Scenario

General Terms

Human Factors, Design, Measurement

Introduction

Increase in human life expectancy in recent years has created a substantial population of senior citizens in most civilized societies. Owing to this fact, healthcare systems are currently under severe stress. One probable solution of the problem can be moving away from a doctor centric system to patient driven operations model with quantitative, predictive and preventive aspects in the whole information flow [30]. The healthcare segment now has to depend more and more on end-user computing devices. The healthcare industry is witnessing the emergence of miniaturized wellness devices that can capture vitals in real-time and communicate to a back-end over distributed heterogeneous environments for analytics. However, apart from monitoring wellness parameters, day-to-day monitoring of activities and location of elderly people and chronically ill patients are also important as they are often living alone and are prone to emergency conditions.

A study on the topic reveals that extensive research has been done on many experiments with miniaturized sensors, either wearable or concealed, including deploying cameras at different strategic points. Though technically proven, the solutions have failed to excite both the industry and the consumers, as they are often cumbersome to deploy and come with huge infrastructure cost (both deployment and maintenance). Machine-vision based solutions suffer from privacy issues. This has motivated us to work on the challenge of bringing ubiquity in elderly people and chronic patient monitoring. We have named our project UbiHeld which is a loose acronym for **Ubi**quitous **H**ealthcare for the **Eld**erly. UbiHeld tries to solve the said challenges by using smartphones, Kinect based depth sensors and the user's social network in tandem.

In UbiHeld, the smartphone is used as the primary sensor for getting health related info. The Kinect acts as aided sensors which use machine vision without compromising privacy, as they work only on depth data and skeletal points rather than people images. Finally social networks are being used as a soft sensor for psychoanalysis and augmenting smartphone and Kinect sensor data. The differentiators in UbiHeld are replacing medical devices of elderly people and chronically ill patients at home with smartphones, which reduces cost and cognitive load on subjects. UbiHeld acknowledges that subjects may not carry phones at all places within home, and aims on solving that by placing Kinect sensors at strategic points. The observed sensor data from Kinect and smartphone are fused to get a complete picture.

Another differentiation is using social media as ubiquitous sensor to gain insight into patient's psychological state to augment the physical sensor data. NLP (Natural Language Processing) is used to monitor health by inferring from social media such as blogs, microblogs, posts and comments. A simple *'Get well soon'* comment in social network site is an indication that the person being referred to is suffering some ailment and the progress of the healing may be inferred by looking at the persons and her friends posts over a certain period of time. An IoT (Internet of Things) platform code named RIPSAC (Real Time Integrated Platform for Services and Analytics for Cities) [24] is getting used as the back-end for fusion of the sensor data and application deployment. [4, 8] shows how a general remote patient monitoring architecture addresses both problems of elderly and chronically ill people at their home environment. In similar

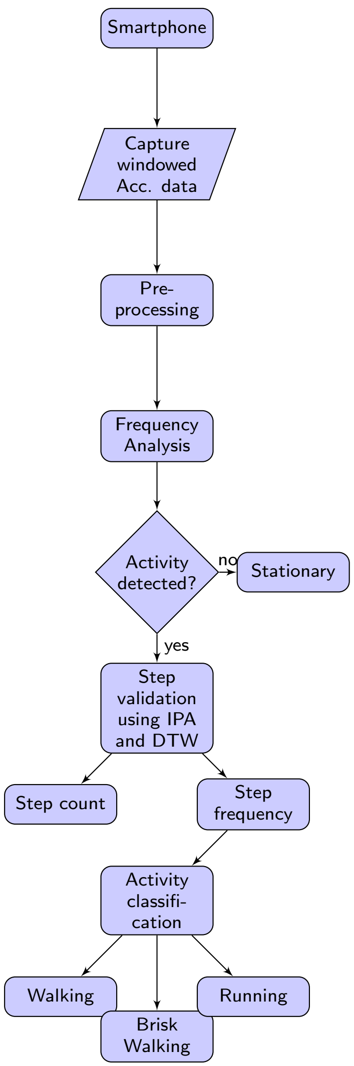


Figure 2: Block Diagram of Activity Classification and Step Count

fashion, UbiHeld also addresses both the problems with a single solution.

The paper is organized in four sections. The *'System Overview'* section explains the high level architecture. The *'Methodology'* section explains in detail all the sensing components along with the visualization components in the back-end citing the prior arts. Then we present and analyze the results we have achieved so far in *'Early Results and Analysis'* section and draw our conclusion and future roadmap in *'Conclusion and Future Roadmap'*.

System Overview

UbiHeld is a set of multiple heterogeneous sub-systems working together to provide desired results. Figure 1 shows the various components of UbiHeld in the final deployment scenario. It is designed with the assumption that the subject will carry a smartphone 24x7 except while sleeping or visiting toilet. Kinect is used to detect the sleeping patterns of the user in bedroom and the frequency and duration spent in toilet. Additionally, Kinect will also be placed at the living room with the couch in radar, which will detect the subject's habit of reading, watching TV and sitting idle etc. Kinect at bedroom/living room shall also cover subject's medicine counter to assure that subject takes his or her regular medicines. In all other places not covered by Kinect, the phone inertial sensors are used for indoor localization and activity detection e.g. walking, sitting, standing and fall. The importance of these parameters in healthcare monitoring and wellness has been discussed in prior research works [14, 9, 11]. Finally, the facts are augmented with observation from subject's social network feed.

The overall architecture is shown in Figure 3. The smartphone and Kinect are used in tandem to detect location and activity. The Kinect controller connects to the back-end using WiFi, whereas the smartphone uses either WiFi or mobile data services for the same. Calculations like step counting and activity detection are done locally on the smartphone and the resultant output is stored in the back-end as sensor observed data. Similarly for Kinect, the people identification and activity detection is locally on the controller platform. The social network application captures user text data and transfers the posts to back-end for analysis using NLP techniques. The final piece is the analytics module which generates the final results to be provided to the consumers which may be patients, caregivers, medical practitioners or insurance companies. The analytics module performs fusion of the long term data from smartphones, Kinects and Social Network to derive the normal and abnormal behavioral patterns of individuals.

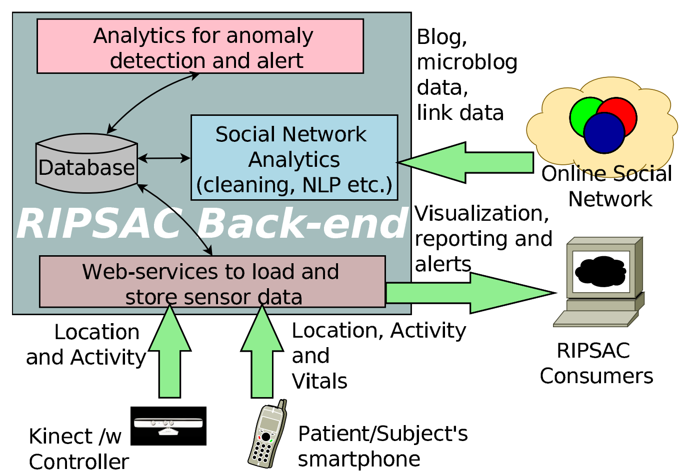


Figure 3: Ubiheld - Architecture Diagram

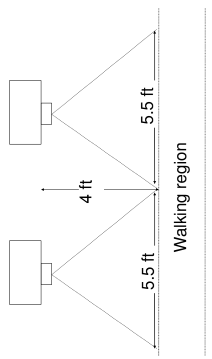


Figure 4: Setup with Multiple Kinects for Increased Field View

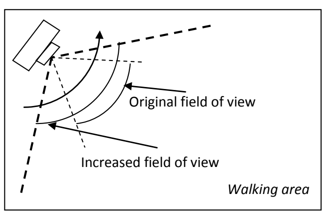


Figure 5: Setup with Rotating Kinects for Increased Field View

Various components of UbiHeld are discussed into following subsections:

The Smartphone
In UbiHeld, the smartphone plays multiple roles. As shown in Figure 2, it is used for activity detection and uses the steps counted for localization. It can estimate postures like sitting and standing. The walking steps are used to find calories burnt by the user during morning/evening walks. Further the smartphone camera is used to detect physiological properties e.g. Heart Rate (a.k.a. Pulse Rate), SpO2 (Oxygen Saturation) and BP (Blood Pressure). The smartphone is also used to collect vitals from medical instruments connected over Bluetooth/WiFi like in [6, 16].

Kinect with Controller
The Kinect platform is a depth sensing system armed with IR (Infra Red) sensors. Although primarily commercialized as a gaming accessory for Microsoft X-box, it has been used by the scientific community as a camera based sensor for people identification and activity detection. In UbiHeld, the Kinect is supposed to perform localization of the subject accurately within its periphery of vision. Activities like watching TV, reading a newspaper/book, consuming medicine, visiting toilet and sleeping are captured using Kinect. Since Kinect comes only with a USB interface, a controller platform (a low-cost computing device) is attached to it and equipped with a WiFi antenna to send data over to the back-end server.

Social Sensing
Social sensing is a component of UbiHeld that acts as a soft-sensor. It resides as a personal application on the subject's social networking site, where the user has to allow the application to access his or her posts, both private and public, and to send the info to the backend server of UbiHeld for further processing. All these posts are analyzed in the backend, and the resultant observation gets posted in the IoT database as a healthcare sensor data. This allows UbiHeld to gauge mental condition of the subject and augment the physical sensor data observed from Kinect and smartphone.

The Backend Server
The backend server of UbiHeld is implemented on the RIPSAC [24] platform, which includes an implementation of OGC (Open Geospatial Consortium) standards for sensor data storage and analysis. It also has application deployment facility. The use of OGC standards has facilitated the integration of inputs from a wide variety of sensors to be stored and analyzed in a seamless fashion. Sensor data is gathered on the server and fused to get the final location and activity, based on confidence scores reported by individual sensors. For notification and alert generation, it uses Sensor Event Service (SES) [3], which is based on publisher subscriber model with different filter levels for notifications. The information producers register to SES and publish the events, where as notification consumers subscribe to the events, with appropriate filter levels (to receive only relevant events that satisfy the filtering criteria). Further it allows visualizations based on the same for remote monitoring of patients. Patterns are also created based on regular behavioral trends and the same is used to detect anomalies and raise alerts. High priority alerts like fall detection etc. are routed via server directly to the caregiver or the medical personnel.

Methodology
As touched upon in the previous section, every component in UbiHeld performs a set of functions which contribute to the sphere of healthcare and wellness monitoring. In this section, we elucidate the functionalities in greater detail.

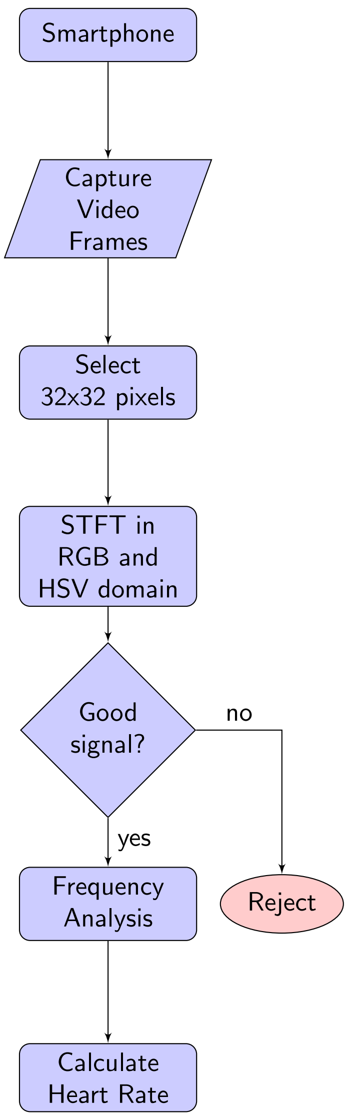


Figure 6: PPG based Heart Rate Detection

Kinect Based Identification and Localization
Kinect is used to extract the skeletal joints of human being as 3D points using the Microsoft SDK [1]. The motion of these skeletal joints is used to identify and localize an individual. Several works have been done on the identification area [20, 28], where either unsupervised or supervised techniques are used. All of them have a constraint on the walking pattern of the individual either side walk or front walk. Though Naresh et.al [20] attempted for an arbitrary walk but they restricted the individuals to walk in a predefined specific path. However, it is very important to get rid of all these constraints for a successful deployment.

In order to get rid of the above limitations, a pose based approach is being experimented. Initially the static and dynamic features, R^{46}, [28] are extracted from the frame level data. The static features are unique and fixed for an individual. The dynamic features vary with time due to the walking patterns. However, there are certain unique poses that characterizes an individual. Hence the dynamic features are clustered, using K-means [18] clustering, into certain key poses. The static features and the centroids of the clusters obtained from the dynamic features are used for SVM [12] training with radial basis function (RBF). The trained model is later used for recognizing an individual. Moreover, due to the limited field of view of Kinect we are experimenting with multiple Kinect or a rotating Kinect placed in a corner of a room as shown in Figure 4 and Figure 5 respectively.

Kinect Based Activity Detection
A good survey on the human activity recognition using depth image is given in [10]. However, it does not cover the usage of Kinect. Skeleton based human activity detection is studied in [29], where the Kinect is mounted on a robot. The challenge is to minimize the number of Kinects to cover various activities of elderly people at home. In order to judiciously partition the processing between the Kinect Controller and the RIPSAC platform at back-end, the skeleton data and quantized depth data are extracted by Kinect controller and sent to the back-end server. Using this data, activity detection is performed in the back-end server. Moreover, as the RGB video information is not sent to the back-end server, the privacy information is greatly preserved.

Mobile Phone Camera based Physiological Sensing
A pulse oximeter unobtrusively monitors volumetric change in flow of blood by capturing PPG (photoplethysmogram). The underlying idea can be further extended by capturing the video of a user's fingertip and using that to estimate different physiological parameters e.g. Heart Rate (HR), BP, SpO2 etc. Recent studies ([27, 19]) reveal that a mobile phone camera is adequately capable of recording such videos.

Correct placement of the camera is an issue and to mitigate that in UbiHeld, we have proposed a state machine which differentiates the acceptable signal from the poor signal using multiple-windowed short-time Fourier transforms [25]. As shown in Figure 6, we have approached the detection of onset of good signal using both RGB and HSV spaces.

Inertial Sensor Based Localization
Inertial sensors can be used for localization using several techniques and one such approach deployed by UbiHeld is the use of step-detection. Once the smartphone application is able to count the number of steps as well as estimate the stride-length using either training or gait estimation from Kinect based video, the displacement can be calculated with the help of magnetometer which

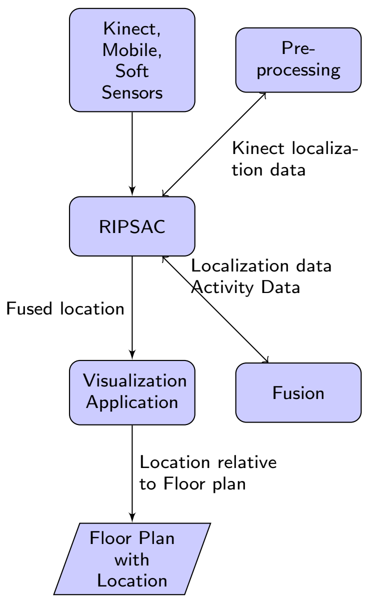


Figure 7: Back-end Processing Steps

provides heading direction. However inertial sensors suffer from *drift* resulting in erroneous output. Li, Fan, et al. [21] provides a method on similar lines which uses particle filters for correcting accelerometer errors using the floor plan as a guide.

It is to be observed that the use of particle filter alone can provide good results in an office space with closely linked corridors and small cubicles but not in a home scenario with living rooms and open spaces. One low-cost solution can be putting external permanent rare-earth magnets. Tremp, Patrick [32] gives an indication that this approach may be feasible.

Inertial Sensor Based Activity Detection
As shown in Figure 2, UbiHeld collects real-time windowed accelerometer signal which goes through several levels of pre-processing e.g. zero normalization, linear interpolation and low pass filtration. The activity classifier determines the activity type like walking, brisk-walking, stationary etc. These step and activity parameters are used for estimating the calorie burnt by a subject during a session of walking [17]. Foreyt [15] provides a simple relation between number of steps and calorie burnt, which is supported by [31]. Ubiheld uses the same method to calculate calories for a session of walking by elderly people.

Further, the inertial sensors can also be used for posture detection like sitting, standing and walking as provided by [22]. Finally, detecting falls which is a major concern for elderly people can also be achieved using inertial sensors on the phone [7].

Social Network Analysis
Perception, behavior, aspirations, motivation, interest, obstacles and struggle are some of the factors which can be mined from social media, and have a definite bearing on the health of a person [5]. Research study [26] mentions an explicit link between emotions and physical health and put much emphasis on daily emotions as one of the important health factors. [5] suggests that lifestyle and behavior information of a patient is important to gain additional insight to health factors and social media is a vital source of this information. An application hosted on a social network platform with proper privacy preserving schemes in place can detect emotion from the posts of the application subscribers and provide them to the back-end as a sensor observed data with parameters like emotion polarity, emotion shade and emotion intensity.

Backend Server Based Processing
As shown in Figure 7, data from multiple and heterogenous sensors flow into the RIPSAC back-end. This requires the backend to be intelligent. For example Kinect reports location considering itself as the origin, hence we use a preprocessing step involving origin shift using a typical transformation matrix to bring it into floor-plan coordinates. Also the location and activity data is overlapping in nature. This requires a fusion module to stitch together split views into a more accurate and "big-picture" view. To achieve this, a confidence score based fusion mechanism is used. In general, Kinect reports events with higher confidence in its field of view than inertial sensors of smartphone.

The daily data is periodic in nature and reflects the routine behavior of the monitored subject. Hence UbiHeld is designed to learn the routine behavior of the monitored subject. Activity patterns are mined and the same is used to model the subject. Any significant and abrupt change in the modeled parameters is bound to violate the model and hence considered as anomalous condition. An event based rule engine is responsible for acting on the condition

Subjects	1	2	3
Detected steps	142	116	79
Actual steps	133	117	76
Estimated Energy (kCal)	7.1	5.8	4.0

Table 1: Calorie Estimates for Step Based Activities

Subjects	1	2	3
Actual HR	90	71	99
Detected HR in RGB	94	158	77
Detected HR in HSV	91	70	105

Table 2: Calculation of Heart Rate from PPG signal

Sub	a	b	c	d	e
a	2478	0	4	0	0
b	0	2415	4	0	0
c	0	0	2451	0	0
d	0	0	4	2328	0
e	0	0	4	0	2484

Table 3: Confusion Matrix for People Identification

by publishing the same to SES. A subscriber to the anomalous events may be a doctor, a care-giver or even a medical insurance company, depending on the use-case. High priority events like fall detection require immediate attention and hence, they are published in real-time and to facilitate rescue of the subject, a web based dashboard application is designed which shows the indoor location of a monitored subject on a floor plan in near real time.

Early Results and Analysis

In this section, several early results related to the methods described in previous sections are provided. The first result presented in Table 1 represents calorie count using our step detection and estimation method from phone inertial sensors. As mentioned in [15, 31], when the activity gets classified as *'walking'*, 2000 steps amount to 100 kCal. As shown in Figure 3, the phone sensors detect the steps and send the same to back-end. The back-end runs offline analytics on the steps counted for the elderly person over the day and reports calorie results back to the dashboard application.

The results for obtaining HR from the PPG information are shown in Table 2. It can be seen that the HR calculated in HSV domain is closer to the actual values than in RGB domain. Similar to the above use-case, PPG calculation is done on the smartphone and the pulse data is stored in back-end storage where anomaly detection algorithms run to generate reports and alerts.

Table 3 shows the confusion matrix for people identification, using pose based approach on Kinect data along with SVM classification using RBF. The diagonal entries indicate the correct number of frames for each identified subjects (a to e). The ab-diagonal entries indicate wrong detection. The average F-score is 0.996 which indicates that this can be used for practical applications. If we map this to Figure 3, the pose detection, identification and localization are done in Kinect controller. These data are sent to backend server for fusion with other sensor data and long term analytics.

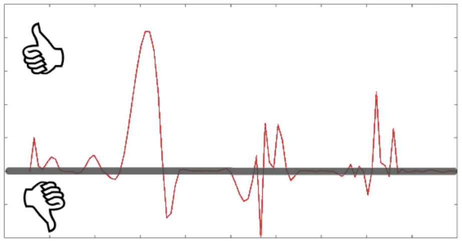


Figure 8: Mood variation of one of our facebook app subscribers during a period of 7 months (horizontal line depicts neutral mood)

For social sensing, we have used Lingpipe package [2] for polarity analysis. SentiSense affective lexicon [13] based approach was used in association with wordnet [23] word sense disambiguation to detect fourteen distinct type of emotion shades. We have developed a Facebook application and all members from our lab have subscribed to this application and given permission to access private and public posts. We are currently experimenting with emotion intensity using lexicon based approaches in addition to word sense disambiguation. In future we wish to extend our social media analysis to cover additional lifestyle and behavioral factors as suggested by [5]. Figure 8 shows the polarity curve drawn against timestamp for a particular subscriber of our facebook application.

The localization experiments were carried out in a typical office space with a person carrying a smartphone. The inertial localization coordinates were posted to the

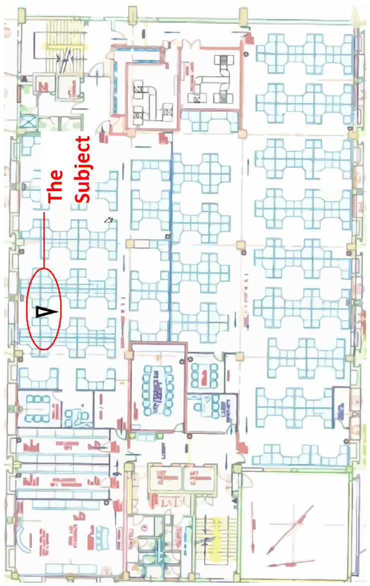
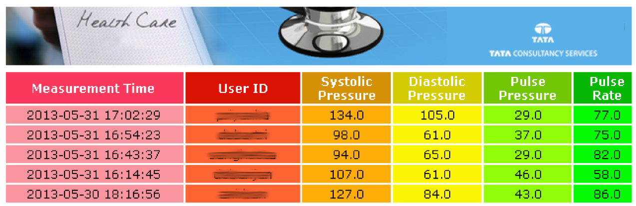


Figure 9: Screenshot of Visualization App

back-end server and finally the UbiHeld web visualization portal can be used to view the subject roaming on the floor plan of his or her home. The floor plan is converted to SVG and the SVG coordinates and paths are used as a tool to visualize the subject.



Health Care
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Measurement Time	User ID	Systolic Pressure	Diastolic Pressure	Pulse Pressure	Pulse Rate
2013-05-31 17:02:29	[redacted]	134.0	105.0	29.0	77.0
2013-05-31 16:54:23	[redacted]	98.0	61.0	37.0	75.0
2013-05-31 16:43:37	[redacted]	94.0	65.0	29.0	82.0
2013-05-31 16:14:45	[redacted]	107.0	61.0	46.0	58.0
2013-05-30 18:16:56	[redacted]	127.0	84.0	43.0	86.0

Figure 10: TCS Health Portal

A java servlet based implementation is shown in Figure 9. This is a part of visualization and reporting services as per Figure 3. The same service is used to create the dashboard in Figure 10 which is a web portal containing vitals of various subjects over a period of time. This dashboard is available to RIPSAC consumers.

Conclusion and Future Roadmap

The aim of UbiHeld is to collect sensor data ubiquitously from all kinds of possible sources for arriving at a conclusion on the health status of elderly people or a chronically ill patient residing at home. The early results from the experiments carried out with smartphone and Kinect are quite encouraging. Since the project deals with human conditions, extreme caution is being taken before piloting with actual patients. Research on using social network data for healthcare is in very early stage and so we are consulting physicians, especially psychiatrists. Till now all experiments have been done on volunteers from the team. All the results achieved so far have some constraints like placing the smartphone in a particular body region or placing the Kinect sensors at a particular lighting condition or using a controlled group of users in social network. To make UbiHeld truly ubiquitous and achieving its ultimate aim, these restrictions need to be lifted in the future. On the server side, so far we only have reported the sensor data and demonstrated the same via visualization.

In future, data from different sensors need to be fused and used for attaining the project objective. UbiHeld will be equipped with more intelligent alarms, alerts and anomaly detection analytics on the backend, based on activities, physiological and psychological parameters. We further believe that day-to-day monitoring data will be highly useful for medical practitioners while performing diagnosis and further treatment on such subjects. Also UbiHeld will evolve to capture more and more physiological parameters using a variety of sensors on the smartphone like unobtrusive glucometry and ultrasound scanning. Finally, UbiHeld will be able to identify and classify much greater amount of human activities for a more detailed and specific analysis of a wide variety of chronic diseases like hypertension, diabetes etc.

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