Solution Design Document

A Project/Internship by Intech Olympiad

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Solution Design Document

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Team ID: E2

Members:

1. **Aditya Sangale**
2. **Gauri Lodha**
3. **Anushka Deshpande**
4. **Dhanshri Rajput**

Mentor:

Ravindra Arun Moholkar

Version	Date	Change List	Modified By
1.0	24/06/2020	Initial Draft	Aditya Gauri
1. 1	24/06/2020	A. Submission of synopsis	Aditya Gauri
1.2	1/07/2020	B. The reorganized section on Component Design. Common Guidelines for all Component Design sections are added. Added process flow charts, modified component designed for the product prototype.	Aditya Anushka Dhanshri

Problem Statement:

- Project Title / Impact Area:

Tracing contacts post opening up of lockdown.

- Present Challenges:
    - Post COVID-19 lockdown, social distancing will not be followed at malls, theatres, restaurants etc. ○ If a person is found to be infected, it is difficult to trace where (and when) he / she has been in the past 15 days when he / she was carrying an infection.

- Points to be addressed by proposed solution to overcome challenges:

    - Use a wearable and by creating a platform that uses google timeline, trace where a person has been in the past 15 days (including timestamps).
    - Use this timeline data to enlist who else has been near the locations where the infected person has visited. ○ Use the wearable to trace where he / she has been moving if kept in a quarantine.

Project Background

Tracing contacts post opening up of lockdown -Post COVID-19 lockdown

Post opening up of the lockdown, since many people would come in contact with each other without following any social distancing, the COVID-19 virus would spread rapidly which would pose a great risk of huge masses getting infected.

In such a situation, tracing the people who have come in contact with the infected person would be very challenging and hence controlling the spread of the virus would be very difficult. More people getting infected would result in more people getting quarantined which would result in the reduction of manpower and eventually have an impact on the economy. If contacts are traced, we can avoid the spread by alerting the people nearby the infected person and hence avoid any potential loss.

Introduction:

Smartphone and smartwatch technology is changing the transmission and making monitoring more easily for patients and research participants to extract their healthcare information in real time and further apply it. Flexible, bidirectional and real-time control of communication allows development of a rich set of healthcare applications that can provide interactivity with the participant and adapt dynamically to their changing environment. Additionally, smartwatches have a variety of sensors suitable for collecting physical activity and location data. The combination of all these features makes it possible to transmit the collected data to a remote server, and thus, to monitor physical activity and potentially social activity in real time. As smartwatches exhibit high user acceptability and increasing popularity, they are ideal devices for monitoring activities for extended periods of time to investigate the physical activity patterns in free-living condition and their relationship with the seemingly random occurring illnesses like COVID-19, which have remained a challenge in past few months. Therefore, the purpose of this project is to develop a smartwatch-based framework for real-time and online assessment and monitoring. The proposed framework will include a smartwatch application and server. The smartwatch application will be used to collect and pre-process data. The server will be used to store and retrieve data, remote monitor, and further sent to the client processed with result and to propose required precaution to be taken.

Rationale

As technology continues to evolve, more and more physical devices are being integrated with sensors and connectivity. This growing network of devices able to connect and exchange data has been termed the Internet of Things, and will ultimately lead to high-fidelity data collection on a variety of healthbased outcomes at the population level. At present, such connected devices offer researchers the immediate benefit of free-living data collection in the absence of direct physical contact with the device or participant.

Previous reviews on smartwatches have found that although there have been several research studies that involve the use of smartwatches, very few have been tested beyond feasibility but given the Outbreak of COVID-19 the research have been fast-forwarded and many tech companies have launched similar products including tech giant Apple. This project looks further into the technology utilized behind each smartwatch sensors, type of smartwatch used, and the features that were most important for classification and further ways to make it cheap and affordable to common people. We will also examine the current smartwatches on the market to see what other sensing mechanisms and features of the watches may be beneficial to healthcare applications and how they fit in current clinical trial project design.

In fact, modern mobile devices (e.g., smart devices) offer a convenient platform that includes power computational abilities, high-speed connectivity, adequate storage, and a wide array of sensors. Unlike more specialized devices for data collection (e.g. Fitbit) that are focused on one domain (i.e. accelerometer-based activity monitors), smart devices combine power and flexibility with a variety of sensors that provide the necessary framework for a more comprehensive approach to remote personal health monitoring. Moreover, this approach also provides several major advantages over traditional methods including the ability to customize apps through the Application Program Interface (API), a screen interface for displaying information and interacting with participants, a physical input option (e.g. turn dial bezel), the large number of sensors, and the potential to have remote connectivity and control of sensors.

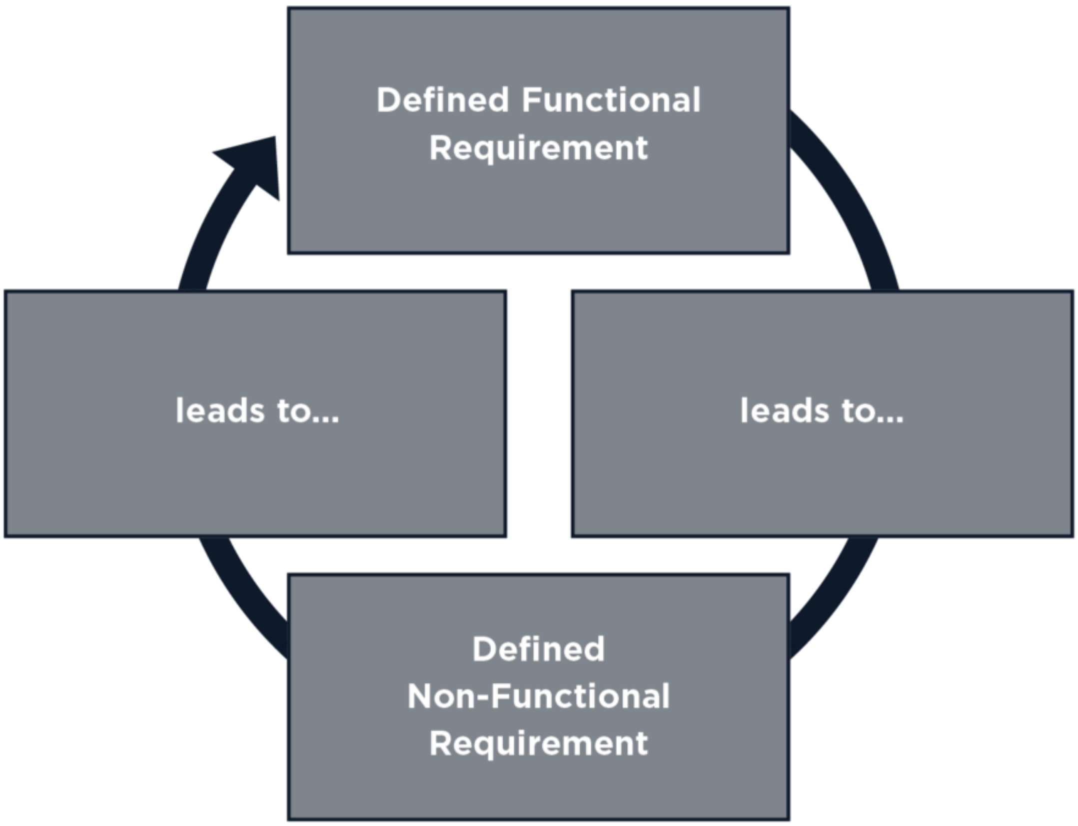
Smartwatches are convenient to wear and have the capability to collect data in a continuous manner given that the battery is charged periodically. Furthermore, they provide additional benefit to the participant including managing their calendar, text messaging and making phone calls which can have a significant impact on their acceptance and wear time. There has been a growing interest in adopting smartwatches for research on behaviours and mobility patterns. While their convenience in wear and continuous data collection capability already make them a lucrative research tool, their ability for remote access and control of sensors along with the potential for direct communication with a user offers seemingly limitless possibilities of additional applications. For example, ecological momentary assessments (EMA) can be incorporated to describe health, symptoms and potential episodic health events that are challenging to capture in real-time (e.g., falls, hospitalizations). The concomitant collection of location information via GPS to understand community mobility patterns, physical activity data from an accelerometer and reported health symptoms or events is ideal for creating a narrative of personal health information in a remote and interactive manner.

These mobile healthcare frameworks rely on communication means to obtain vital information from patients in real time and provide warnings and guidelines remotely when data deviate from an expected value. While such frameworks bring merit, there are some gaps in phone-based ascertainment. Smartphones are usually carried in pocket, which is not an ideal location for activity recognition, or in hand-held bags. Therefore, sensor data collected from these devices do not provide information required for activity recognition; especially, for cases where there are only hand movements, such as drinking water. Smartwatches offer a more logical choice because they possess the same sensors and connectivity and are fixed to the body. Despite the benefits, the development of smartwatch apps for data collection has not progressed since their initial consumer release.

In sum, the purpose of this project is to develop the framework for a novel remote monitoring system through the integration of a smartwatchbased application and a remotely-connected server. Such framework will pave the way for additional applications that simultaneously collect data in the target domains of physical activity, mobility, EMA, patient-reported outcomes, and intervening health events.

Exhaustive List of Requirements

While preferring the requirements let's divide them in two categories, namely functional and non-functional requirements.



□ Functional Requirements

- For Application(software)

1. All profile data (e.g. name, phone number, age/DOB, gender, height, weight) should be immediately updated to the server and log of any changes should be reflected as soon as possible.
2. Users should have mobile phone (iOS or android) with internet connectivity.

3. Location access permission has to be provided by users.
4. Bluetooth connection has be always established among application and watch
5. Real time updating of reports (of heartbeat rate, blood pressure, temperature) of user should be taken care.
6. As the reports cross the set limit alerts had to be generated immediately informing user about steps to be taken in order to help themselves and society.
7. 24x7 support has to be provided to help each user and citizen of country.
8. In addition to support, EXPERT support has to be implemented to give user proper guidelines regarding the healthcare.
9. Current news and news feed about healthcare has to be properly given time to time.

- For Watch(hardware)

1. It should be always connected to the mobile phone for effective results.
2. Watch should consist of sensors such as temperature sensor, heartbeat sensor, GPS and etc.
3. It should be compatible with android as well iOS devices.
4. Proper transfer and immediate updating of results of sensors and GPS.
5. Notifications and alerts have to be also displayed on watch.

- Administration

1. Keep track of all users and there health related data.
2. Report the concern authority once limit of values of report cross of particular user.
3. Continuous tracking of users and notify once near affected user or within range of 1 meter.

- Non-Functional Requirements
  - For Application (software)
    1. User Authentication via mail or AADHAR card.

  - For Watch(hardware)
    1. Integration of more social application like (what’s app, Facebook).
    2. Integration of calling and messaging system.

Identified Scope of Minimum Viable Product (MVP)

In Scope

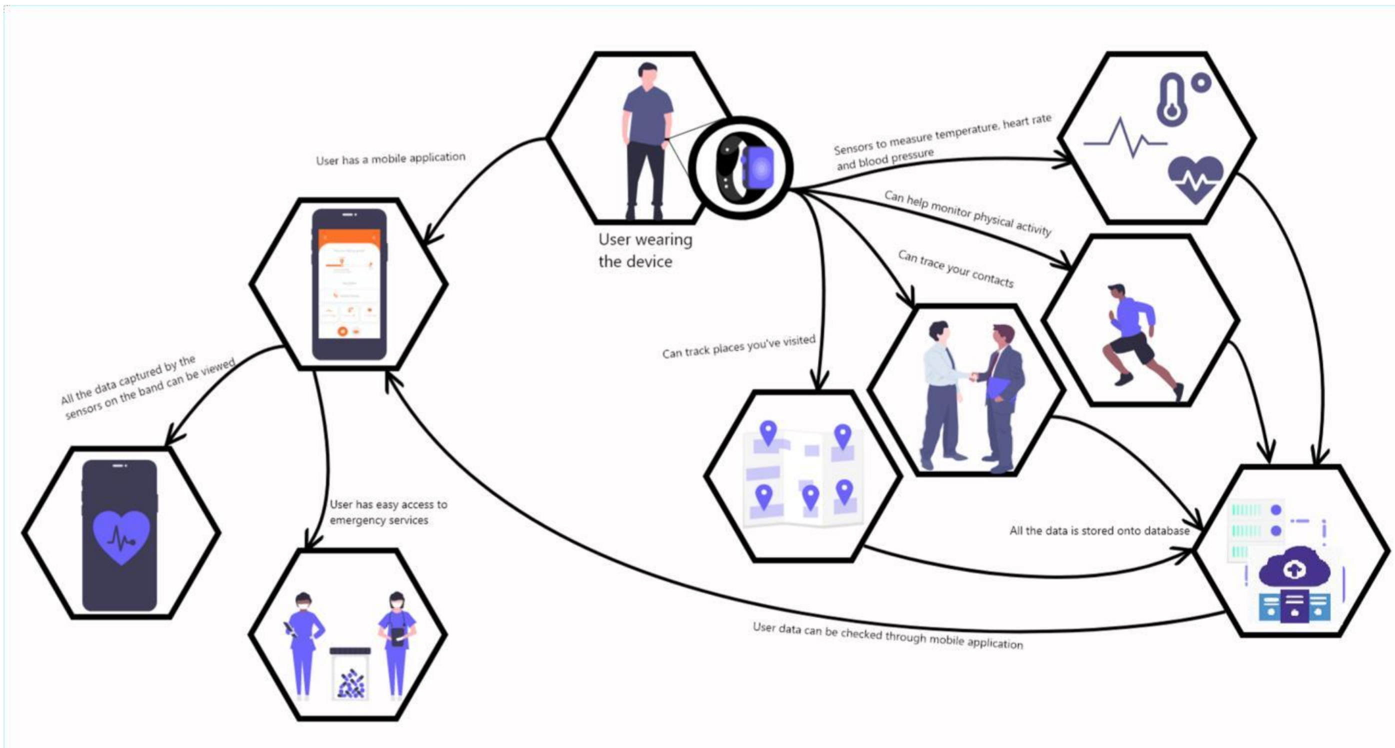
- For Application (software)
  1. It will consist five main tags (HOME Profile, Track, Report, Alerts], MORE).
  2. Under Profile section user has to fill up his/her details such as name, contact details, age/DOB, gender, height, and weight.
  3. In the Track section user will see all the details measured by watch such as temperature of his body, heartbeat rate, BMI etc.
  4. Report section will provide the periodic analysis of user as per the data, and recommend the proper guidelines.
  5. Alerts section plays crucial role by alerting and notifying users with their health according to report generated by Report section and tracking infected person nearby. This section also provides the news feed for current scenario and spread awareness among users.

- For Watch (Hardware)
  1. This is most likely to be similar to the smart watches in the market with additional feature of alerting the user with

nearby affected user. And by providing approximate distance (in radius term) he/she is from that user.

2. Special care has to be taken to not to reveal infected person identity.

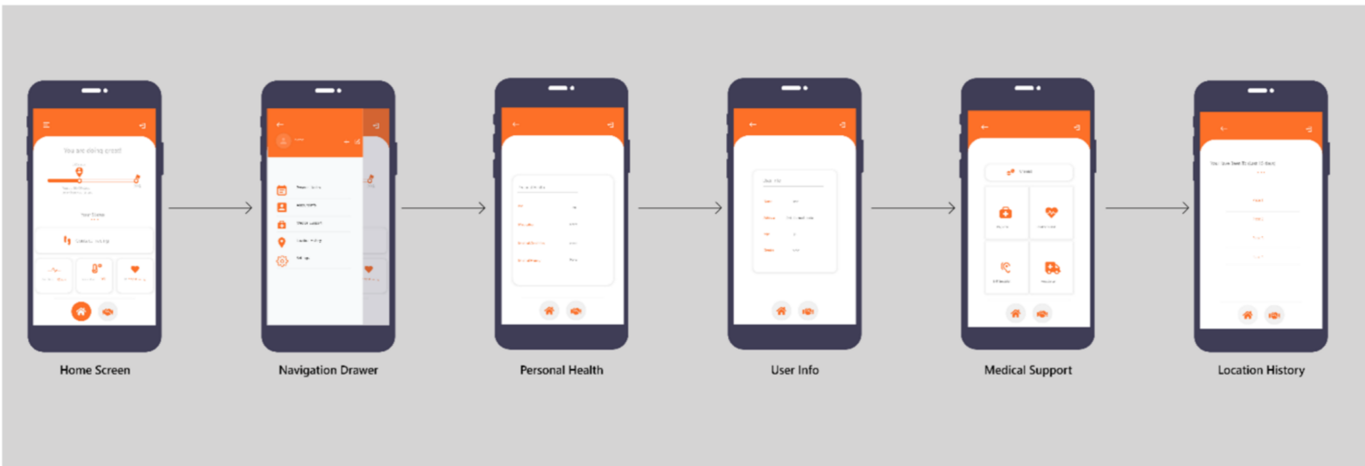
Overall Block Diagram and Process Flow



Description

According to the above diagram, the band will be able to monitor the user's health. It will have sensors in it which would be able to record the temperature, pulses and the heart rate accurately. The band will also track the user's physical activity. User's contacts would be traced by it and stored into database. Additionally, the location history of the user would be maintained. All this data would be stored and the same can be checked on the mobile application that would be installed onto the user's phone. This would enable the users to keep a track of their health and fitness and also be notified of potential risk of acquiring the virus. The users would also get an easy access to all medical facilities like the hospitals, ambulance and also the pharmaceutical stores.

For pure software applications:



The interface of our app would be as above. The home screen would show you whether you are safe from the virus or not. Next your physical activity can be seen .User can set their target and using this app they can monitor their success of meeting the target.

Next the user can check the people they have come in close proximity with and can also know if they have come in contact with someone who has caught the virus. Followed by that user can check their temperature ,heart rate and blood pressure as recorded by the band. Lastly, there are two buttonsHome button and help button.

On the top a navigation drawer button can be seen which has the navigation drawer which houses several options like-Personal health, Account Info, Medical Support, Location History and Settings.

The Personal Health tab gives the user all the information about their personal health like Medications, Medical History, etc.

The user info tab has all basic information like name, address, age and gender of the user

The medical support tab gives the users an easy access to medical services like physician, heart specialist, ENT specialist and also a chemist.
The last tab, the location history tab gives a list of places the user has visited in a certain timeframe.

Component Design 1

Component Design 2

Integration of Components

To accomplish this goal, we present the framework that offers:

(1) A convenient approach for long-term assessment in the context of varying health,
(2) The ability to synchronize sensor data with reports of health events and symptoms (e.g., pain, fatigue), and
(3) Interactive communication in real time, providing an active channel for patient reported outcomes, health events and future intervention delivery.

Knowledge of these domains in real-world scenarios will help understanding the inter and intra-personal factors that contribute to episodic health events.

Smartwatch Features

A. Primary Features

Given the specific healthcare applications above, it is clear that smartwatches have several important features that make them ideal for use in healthcare over the use of smartphones. For instance, smartwatches are able to continuously collect physical activity data, as well as other biosensor data such as heart rate, body temperature, remote blood pressure using external device like pulse oximeter which makes them ideal devices for interventions. Smartphones which require individuals to carry the devices in their pocket or hands, smartwatches can be worn during physical activity and treatment interventions that may require exercise or a high level of exertion by the participant.

In addition to continuous bio-signal monitoring. Furthermore, smartwatches can provide alarms and messages that are more easily seen by individuals during activities such as exercise or interventions, as they can use vibrations, text, and sound to alert the user and provide more immediate communication with healthcare professionals. Finally, after the recent 10.0 Android Wear update, smartwatches now have improved computation power and battery life, allowing them to be used throughout the day and night time to continuously capture information in the community. These features have allowed successful feasibility studies in the aforementioned research, and if battery life is improved, can lead to useful applications that will be tested in clinical trial research.

Resources / Components Dependencies

1. Temperature Sensor for Wearable

Description

This Design is to demonstrate temperature sensoring aimed at the wearables market. The LMT70 temperature sensor is ideal for wearable devices due to its 0.13C temperature accuracy at human body temperatures. Its small form WCSP package allows it to be heated up quickly and thus have a fast thermal response time when placed onto a human body.

Features

a. USB form factor PCB board with breakout tabs to attach different substrates
b. Design report includes thermal response of different substrates and MSP430F5528 ADC calibration techniques
c. This Design system is tested and includes firmware, GUI, User Guides, and a Test Report

2. Heart Rate Monitor (HRM) Bluetooth

Description

This reference design enables a wearable, optimized saturation of peripheral capillary oxygen (SpO2) and multi-sensor, multi-wavelength optical heart rate monitor (HRM). It uses AFE4420 device, which is a single-chip, bio-sensing front end for photo plethysmography (PPG) measurements. It supports up to four switching light-emitting diodes (LEDs) and up to four photodiodes to enable signal acquisition of up to 16 Phases. The CC2640R2F device (supporting Bluetooth® low energy 4.2 and 5) transfers the measured data to a remote location. This patient-monitoring design uses a single CR3032 battery with a 30-day life cycle. Raw data is available to calculate heart rate, SpO2, and other related parameters. 2 on-board light-emitting diodes (LEDs) identify low-battery detection and a Bluetooth connection.

Features

a. Provides raw data to calculate heart rate, SpO2, and other related parameters

b. Uses single-chip, bio-sensing, front-end AFE4420 device for PPG measurement

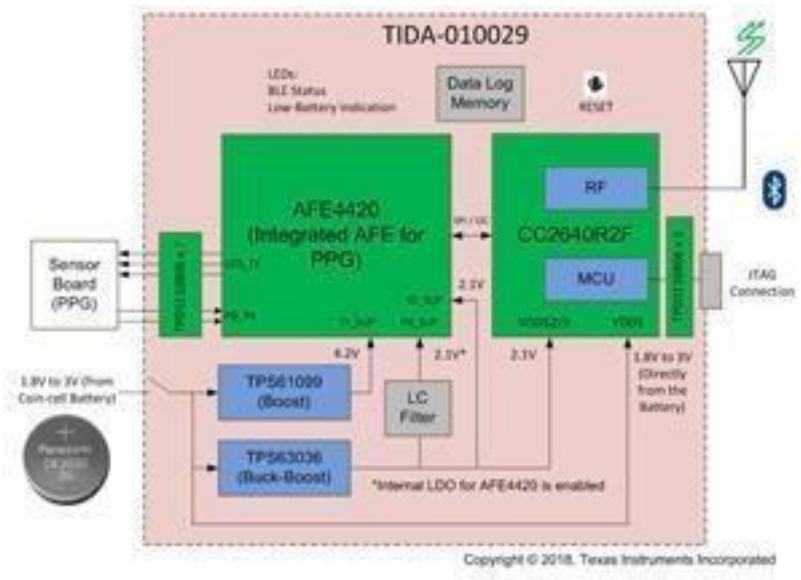
    i. Supports up to 4 LEDs and 4 photodiodes with ambient subtraction to improve signal-to-noise ratio (SNR)

    ii. Enables signal acquisition of up to 16 phases and multi-wavelength measurements with the flexible allocation of LEDs and photodiodes in each phase

c. Integrated Arm® Cortex®-M3 and 2.4-GHz RF transceiver (CC2640R2F) supports wireless data transfer through Bluetooth® low energy 4.2 and 5.0

d. Operates from CR3032 (3-V, 500-mA coin cell battery) with a battery life of 30 days using highly efficient DC/DC converters

e. Small form factor helps in easy adaption to wearable applications



3. Pulse Oximeter with BLE Connectivity

Description

This reference design is for a complete SPO2 Pulse Oximeter finger clip end equipment featuring signal chain, power, and connectivity components. With TI's **AFE4490** Pulse Ox AFE, you can accelerate and simplify your pulse ox design while still ensuring the highest of quality clinical measurements. This reference design also includes a full BLE connectivity design for easy interface to BLE enabled smartwatches, smartphones, tablets, etc.

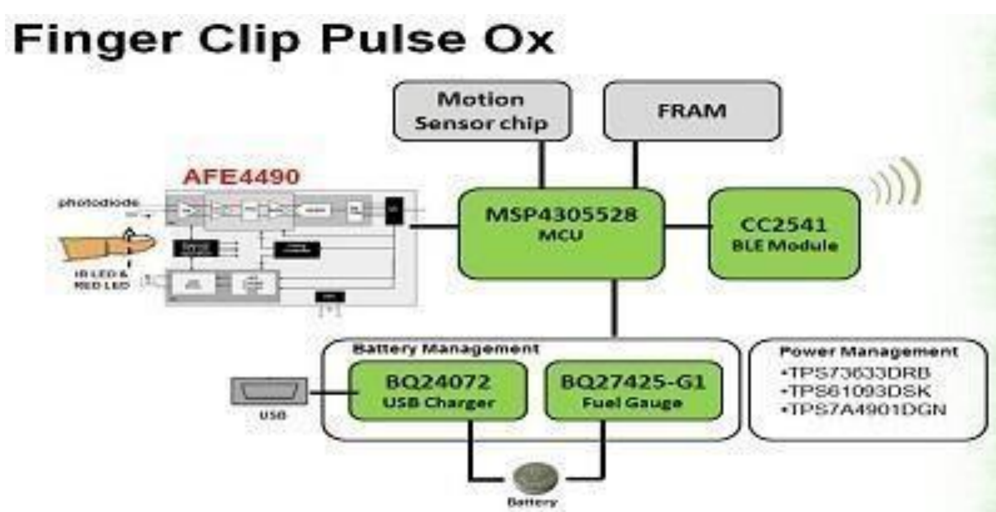
Features

a. Features **AFE4490** for both LED transmit and receive paths of the pulse oxi measurement

b. MSP430F5528 MCU for holding algorithm and calibration data

c. BLE module connection featuring TI's CC2541

d. This design is tested and provides everything you need to complete your design including Schematics, Layout and Gerber files, and BOM

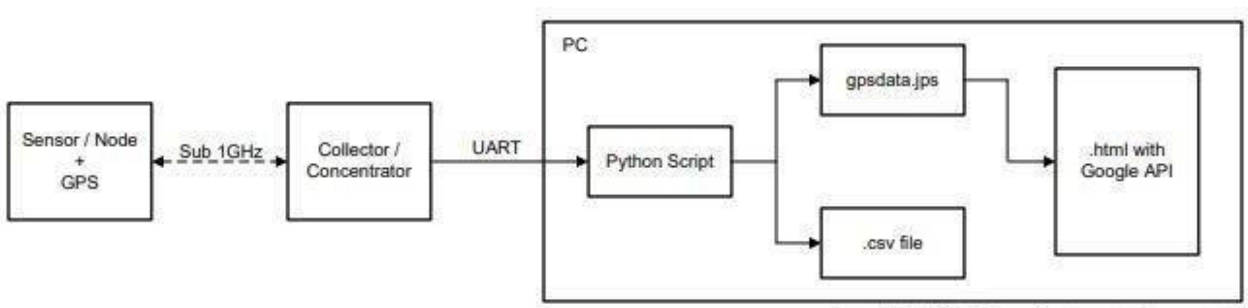


4. GPS Tracking Using Sub-1GHz Devices

Description

Sub 1 GHz wireless radio microcontrollers are becoming a popular choice for many applications worldwide. These devices work on the ISM spectrum bands below 1 GHz, typically in the 769 MHz to 935 MHz, 315 Mhz and the 468 Mhz frequency range, and with the emerging IoT market moving into industrial applications, Sub 1 GHz wireless radio communication are becoming the standard for these applications due to three main reasons:

1. Range
2. Low power
3. Interference



Block Diagram

In this application report, the CC1310 Wireless MCU attached to a GPS module is used, running two different communication protocols in the same Sub 1 GHz band to do range testing and compare the results of both protocols. The CC1310 GPS sensor node connects to the Collector/Concentrator CC1310 using one of the two wireless protocols provided: TI 15.4 Stack or EasyLink. Then, the GPS coordinates are sent in one second intervals. When the Collector/Concentrator CC1310 receives the data, it sends the data through UART to a PC running a python script that collects this data and saves it in a csv file and JSON array. The JSON array is then read by the html page provided and plots the points in a map dynamically.

Added features

1. Smartwatch based fall detection system using deep learning:

This feature will be used to detect if a person wearing the smartwatch fall down in case of severe giddiness, an app that uses accelerometer collects data from a commodity-based smartwatch consisting Internet of Things (Iot) device to detect falls. The smartwatch will be paired with a smartphone that runs the application, which performs the computation necessary for the prediction of falls in real time without incurring latency in communicating with a cloud server, while also preserving data privacy. There have been experiment in the field with both traditional (Support Vector Machine and Naive Bayes) and non-traditional (Deep Learning) machine learning algorithms for the creation of fall detection models using three different fall datasets (Smartwatch, Notch, Far-seeing). The results show that a Deep Learning model for fall detection generally outperforms more traditional models across the three datasets. This is attributed to the Deep Learning model's ability to automatically learn subtle features from the raw accelerometer data that are not available to Naive Bayes and Support Vector Machine, which are restricted to learning from a small set of extracted features manually specified. Furthermore, the Deep Learning model exhibits a better ability to generalize to new users when predicting falls, an important quality of any model that is to be successful in the real world.

2. Smartwatch-based early gesture detection system :

Inertial sensing on wrist-worn devices, such as smartwatches, has recently been used to infer a variety of gesture-driven lifestyle activities, such as smoking and eating. These approaches typically focus on the problem of gesture recognition, i.e., using features defined over the inertial sensor data to identify specific gestures. We could use this feature to track the face snaps and general behavior of the client with their permission. Separately, researchers have investigated the use of such possibly-noisy inertial sensor data to track the hand's 3-D location or movement trajectory, for applications such as pointing based interaction. For these applications, the objective is to accurately track the movement of the human hand, but with latencies low enough to preserve the interactivity of the application. The hand's motions are tracked and integrated into the virtual world, and appropriately projected in the VR display. Accurate tracking of the hand movement is needed to faithfully replicate real-world mechanics—for example, the time instant when the person face gestures when having pain in VR should closely reflect the time that the user's hand would have struck the ball in the real world. At present, such fine-grained hand tracking requires the installation and use of nonportable, custom infrastructure (such as the Kinect depth camera, the Wii Sensor Bar or the HTC-Vive laser tracker). Our goal is to untether the user from such infrastructural components. Instead, the user should be able to simply strap on a VR display and a wrist-mounted device such as a smartwatch, and perform this immersive application at any place.

3. Smartwatch based sign language translator:

Sign language is a natural and fully-formed communication method for deaf or hearing-impaired people. We could use this feature and similar for disabled and old people who have trouble reading and recognizing. Unfortunately, most of the state of the art sign recognition technologies are limited by either high energy consumption or expensive device costs and have a difficult time providing a real time service in a daily life environment. Inspired by previous work on motion detection with wearable devices, we propose a real time robust and user friendly Sign language recognition (SLR) system with affordable and portable commodity mobile devices. Sign Speaker is deployed on a smartwatch along with a smartphone; the smartwatch collects the sign signals and the smartphone outputs translation through an inbuilt loudspeaker.

Supporting POCs

The output of each classifier result will be a strong indicator of the system's ability to predict the legitimate user of the smartwatch. 10-fold-cross-validation will be performed to extract the meaningful information for each legitimate user. In each experiment, the user's data will be split into 10 subsets in which a single subset will be chosen as a validation set towards legitimate user identification and the rest of the 9 subsets will be used as training data to be fed into each classifier individually. Classifier results will be generated with the given setup with every instance in the validation set being classified against the training sets. This entire process will be repeated for every activity and each user and for all three sensors by picking each subsequent subset as a validation set with the reaming as the training set. Leading to a total of 30 experiments for a single sensor's data, 90 experiments for all 3 sensors and 360 experiments for all four classifiers which will be weighted for the final results to identify either a legitimate user or imposture.

Quality Assurance Plan

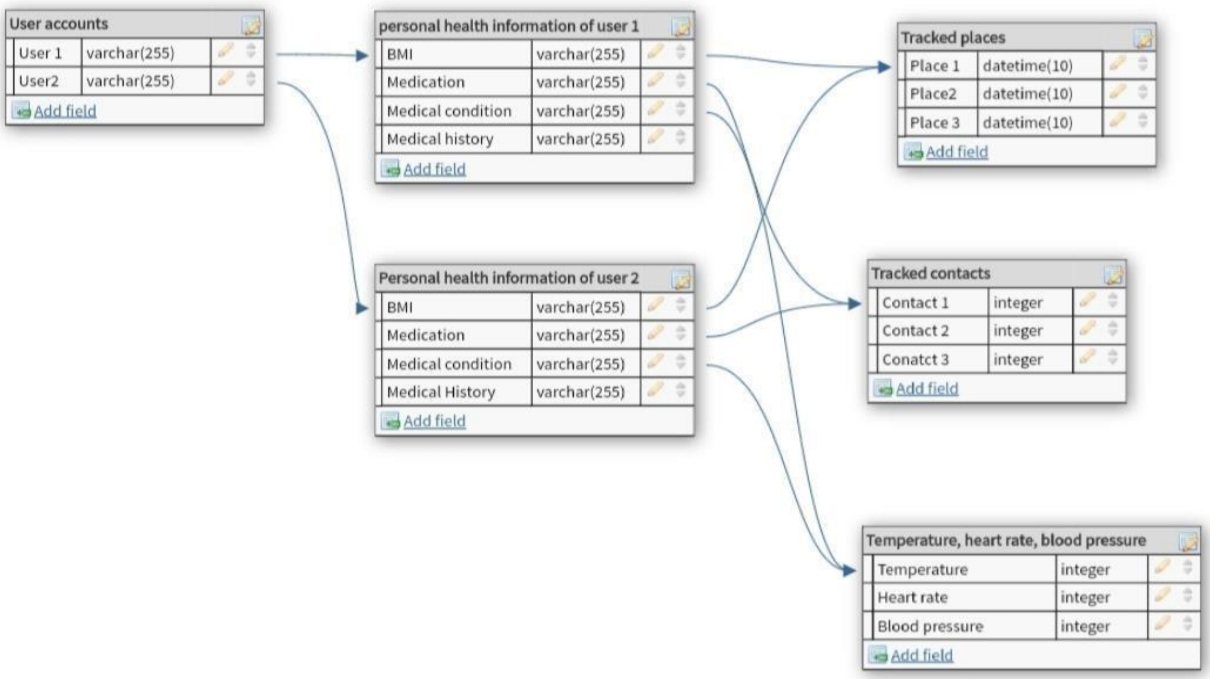
System Modelling:

This section describes the process for collecting the raw signals from different users performing different physical activities under study. This section also explains the process for extracting the meaningful features. Furthermore, we will explain the process of transforming the time series raw sensor signals into examples that can be handled by different classifiers from machine learning literature, for example, Decision Tree (DT), *K*-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Naive Bayes (NB).

Data Collection:

The raw signals will be collected for different activities from various users (female and male) having age from 18-65 years old. The criterion for selecting the subjects was based on gender because different genders exhibit different patterns when performing the same activity. These activities include walking, running, jogging, patients with fever and high blood pressure. All subjects performed these activities twice each day for more than a month. Therefore, the proposed system will utilizes the collected raw data from the same users for the same activity but performed on different days.

The participants enrolled in this study will be approved by the laboratory head. This is a formal prerequisite because the experiments involved human subjects although there was a negligible risk of injury. The involved subjects will be asked to answer a few nontechnical questions about their gender, age, height, weight, left-or-right handedness, and their medical conditions, which will be used as characteristics in the proposed study. Then the subjects will be asked to fasten the smartwatch on their wrist. The device run a simple customdesigned application that controls the data collection process and instructs the participant to add their name and select the activity from the list of five different activities and the sensor from three different sensors mentioned above. Each of these sensors generates 3-dimensional signals and appends a timestamp to the values. After every five minutes, the smartwatch sends the data to the SP, and after a successful transmission, the SP vibrates to notify the user that the data collection process has been successfully completed.



Classifiers:

This work leverages the different classifiers available in Matlab. The literature has highlighted that each classifier will have varying results depending on what the proposed system is predicting. The training process involves learning in relation to the label user wants to predict [26]. For experimental setup, the proposed system involved four different types of classifiers, for example, DT, KNN, SVM, and NB in order to compare the performance.

A. Decision tree

In decision trees, the input space is first separated by class regions to determine the decision tree. Nodes are generated with decision functions that branch depending on the output of a decision. As one traverses from root to leaf, the classifier effectively narrows the prediction space until it reaches its final prediction at the leaf. Decision trees bring scalable and fast implementation with the need to tune many parameters.

B. K-Nearest Neighbours (KNN)

When classifying a given unseen feature vector, KNN will find the *k*-nearest points given a distance function, look at all *k* training labels, and predict the label as the majority of the *k* labels. An advantage of KNN is its robustness against noisy data, and there is only the number of nearest neighbors which needs to carefully tune. It is an instance-based classifier which is also one of the most popular classifiers and is found to be the best in terms of performance and computational complexity as compared to the decision trees.

C. Support Vector Machine (SVM)

SVM recognizes a diverse set of physical activities using motion and other sensors, and the literature has highlighted that their performance is superior to that of the other classifiers [28].

D. Naive Bayes (NB)

NB is a simple and well-known classification method. NB is a probabilistic classifier, and Bayes' rule contains probabilistic models. Bayes' rule relies on the statistical properties of data and the accuracy of data. To begin with, it finds the solution from statistics as well as by data mining. All of these classification methods are suitable for real-time legitimate user identification because they can be generated and evaluated rapidly.

The values used for the different parameters of the classification methods are as follows: SVM is used with a quadratic kernel function; KNN is used with a Euclidean distance function, and nearest neighbors are set to 10; DT is used with 85 as the number of trees. All the said parameters are carefully tuned and optimized prior to the final experimental setups. All the experiments are carried out using Matlab R2014b and installed on core i5 and 8 GB of RAM machine.

Team Member Contribution Details

Name of Team Member	*Role*	*Activities*
1. Aditya Sangale	Leader/Researcher/POC implementer/Documenting	Integration of Components Supporting POCs Quality Assurance Plan Resources / Components Dependencies
2. Anushka Deshpande	UI Designer/ /Developer	Overall Block Diagram and Process Flow Generic Instructions for the Component Design sections below
3. Gauri Lodha	Researcher/POC implementer/ Documenting/ Developer	Exhaustive List of Requirements Identified Scope of Minimum Viable Product (MVP)

4. Dhanshri Rajput	Product Design	Component Design Project Background

Limitations

Why nobody thought regarding the application of smartwatch for monitoring the Covid-19 cases?

Because, Classified applications included activity monitoring, chronic disease self-management, nursing or home-based care, and healthcare education. All studies were considered feasibility or usability studies, and had limited sample sizes. No randomized clinical trials were found. Also, most studies utilized Android-based smartwatches over custom-built, or iOS- based smartwatches, and many relied on the use of the accelerometer and inertial sensors to elucidate physical activities. The results show that most research on smartwatches has been conducted only as feasibility studies for chronic disease self-management. Specifically, these applications targeted various disease conditions whose symptoms can easily be measured by inertial sensors, such as seizures or gait disturbances. In conclusion, although smartwatches show promise in healthcare, significant research on much larger populations is necessary to determine their acceptability and effectiveness in these applications.

Conclusion

The main topic we address in this project is remote health monitoring of the patients impacted by Global Pandemic (COVID-19) and Tracing contacts post opening up of COVID-19 lockdown. The system described in this project uses off the shelf smartwatch and smartphone application, without the need for any custom-made hardware. It enables bidirectional communication, remote measurement of hearth rate, basic activities, accelerometer, gyro eater and magnetometer data, ambient light and atmospheric pressure. It requires minimal change in patient's everyday behavior, and minimal maintenance cost, and thus marks an improvement or alternative to the similar solutions. Smartwatches has become a huge success these past few years and are continued to be popular. This popularity has forced the community to study the security implications of these small and powerful devices. It has been suggested that activity recognition and gait-based identification combined with smartwatches/smart-bands are possible. The proposed system can achieve user identification average accuracy up to 92% with negligible system overhead, minimum time, and power consumption. We hope that the proposed system can act as a key technique for implicit activity recognitionbased legitimate user identification in real-world scenarios. Although consumer-grade smartwatches have penetrated the health research space rapidly since 2014 and given the take of pandemic the research in the related technologies have been fast forwarded, smartwatch technical function, acceptability, and effectiveness in supporting health must be validated in larger field studies that enroll rural and economically backward participants living with the conditions these systems target to monitor with the aid of government healthcare authorities in most of the Third World Countries including India itself.

Information Sources

There have been great deal of research in smartwatch studies for healthcare, we conducted a search for the use of smartwatches in healthcare in the PubMed, EBSCOHost, Springer, Elsevier, ProQuest, IEEE Xplore, and ACM Digital Library databases from 1998 to 2016. The key words we searched were “smartwatch application”, “smartwatch app”, “smartwatch apps”, and “smartwatch healthcare”. Note that we performed the same searches with the key word “smart watch” instead of “smartwatch” for all of the above terms in each database, however, this did not produce any new results and often misinterpreted the search as a “watch” or “smart”, resulting in irrelevant articles. We have used multiple sites and books to gather information regarding the problem statement and have come up with an affordable solution. Neither of the review authors were blind to the journal titles or to the study authors or institutions. Furthermore, a systematic narrative synthesis was provided with information presented in the text to summarize and explain the characteristics and findings. These features included the operating system, type of smartwatch, battery type, connectivity type (e.g. WiFi, Bluetooth, and data communication locations), and its application in Healthcare. In addition, we assessed the important sensors utilized, as well as the important features for classification and use of the smartwatch sensors. These features determined which sensing mechanisms, data communication methods, and feedback types are used in smartwatch based healthcare applications.

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