EasyBand2.0: A Framework with Context-Aware Recommendation Mechanism for Safety-Aware Mobility during Pandemic Outbreaks

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***Abstract*—COVID-19 (Corona Virus Disease 2019) is a pandemic which has been spreading exponentially around the globe. Many countries had adopted stay-at-home or lockdown policies to control its spreading. However, prolonged stay-at-home can cause worse effects like economic crises, unemployment, food scarcity, and mental health problems of individuals. EasyBand2.0 is a wearable personal safety device that helps in social distancing and also helps in safe mobility. Under the IoMT (Internet of Medical Things) framework the wearable EasyBand2.0 device helps in social distancing, it avoids human-to-human contact and helps maintain a safer distance. EasyBand2.0 uses the Low Power BLE technology to sense distance between two user devices and alert them based on the distance and time spent in proximity. Safe mobility of people is also important as travel is resumed in all forms. This paper proposes a software application along with the easy band to further be integrated with a system that works based on GPS (Global Positioning System) or GIS (Geographic Information System) to provide travel logging for contact tracing without exposing personal data. A CARS (Context Aware Recommendation System) based safe zone recommender system is proposed in this paper to aid safe mobility.**

***Index Terms*—Internet-of-Things (IoT), Bluetooth Low Energy(BLE), Social Distancing, CARS(Context Aware Recommender System), COVID-19, Contract Tracing, Data Semantics, RSSI (Received Signal Strength Indicator)**

I. Introduction

COVID-19 (Corona Virus Disease 2019) is a pandemic caused by a newly discovered coronavirus [1]. It is spreading in the human populations in an exponential manner. As governments and health sectors have notified people to maintain hygiene and avoid contact with other people, researchers, innovators, medical organizations and government sectors are pitching in to provide solutions for safety and pandemic management through various technologies like IoMT, IoT, Blockchain, 5G, AI, UAVs etc. Governments, which can no longer afford to keep people under lockdown, are opening with new restrictions and safety measures. At this point of time technology can be made use of to provide a safety system that can help people and countries to get back to operational conditions. In the absence of a vaccine, social distancing was considered as the most effective measure to stop the spread as it reduces human-to-human contact. In the current scenario where vaccines are available, social distancing is still necessary in places which have limited testing facilities, minimum medical assistance and minimal access to vaccination.

II. Soial Distancing during COVID-19 and the Enabling Technologies

Many countries quickly came up with applications based on contract tracing to help identify infected people and their travel history through GPS, GIS and Bluetooth based systems along with organizations which are coming up with wearable devices for pandemic management. Under the Smart Cities umbrella we can always rely on the enabling technologies to design and develop applications that are user friendly and energy efficient [2]. Some of the technologies that aid development of applications for effective social distancing and alerting systems are based on wireless technologies like Wi-Fi, Cellular, Bluetooth, Ultrawideband, GNSS, Zigbee, RFID, etc. [3]. Image and Visualization technologies are also being employed for monitoring social distance and also face mask detection to ensure people are following the COVID-19 safety measures [4].

III. Related Prior Research

There are many solutions researched and proposed for social distancing, especially in pandemic situations. EasyBand is a wearable device proposed in [5]. EasyBand is a standalone device without mobile phone dependency that enables auto-contact tracing and social distancing. One research proposes a Deep CNN (Convolutional Neural Network) social distancing method which uses video feeds from public spaces; a YOLOv3 algorithm is used to detect the humans in the video frame and estimate the distance between them [6]. This research focuses on spaces with video surveillance and monitoring. Another such image based social distancing research is proposed in [7]. This method employs a stereo vision enabled real time human distance measurement. Another research based on object detection from video feeds is [8]. This application detects every person in the feed and tags them with a unique ID. A system that uses BLE (Bluetooth Low Energy) and Wi-Fi to monitor social distancing is proposed in paper [9]. A work that uses RSSI to develop a Local positioning system using Wi-Fi nodes is presented in [10]. A comparative summary of these works is shown in Table I.

Table I
COMPARATIVE TABLE FOR STATE-OF-THE-ART LITERATURE.

Research	Medium	Algorithm	Application
Tripathy et al. [5]	Sensors and BLE	RSSI	Indoor and outdoor spaces
Hou et al. [6]	Video Feed	Deep CNN	Public spaces
Ziran et al. [7]	Stereo Vision	HOG algorithm	Public spaces
Sharma et al. [8]	Video Feed	DNN	Public spaces and Indoor spaces
Kobayashi et al. [9]	BLE Packets	RSSI	University Campuses
EasyBand2.0 (Current Paper)	BLE signal	RSSI	Indoor and Outdoor Spaces

IV. NOVEL CONTRIBUTIONS OF THE CURRENT PAPER

Though there has been much research that proposes applications for social distancing, the solution we are looking at is more feasible and easily deployable. The novel contributions of this proposed method are:

- Bluetooth based distance estimation using RSSI (Received Signal Strength Indicator).
- Log Normal Shadow Modeling for distance estimation.
- An alerting mechanism which notifies the user of different conditions during contacts, like safe, mildly suspect, and highly suspect.
- A vibrator to alert the user of proximity to a suspect.
- A Context Aware Recommender System designed on the 5W-1H code dimension tree model for safe mobility.

A. Problem Addressed in the Current Paper

With social distancing becoming important in curbing the spread of the pandemic, there is a need for better solutions, that are low cost, low power consuming and easily deployable and adaptive. The following are the problems addressed in the current paper.

- The need for a user friendly and more approachable design.
- Low cost and low power consuming application.
- Easily deployable, interoperable and adaptive application.
- Safety-aware application that aids in safe mobility.

B. Solution Proposed in the Current Paper

EasyBand2.0 is designed to be low power consuming, easily deployeable architecture, and a system for recommending to enable safety-aware mobility. Our main contributions are as follows:

- GPS based Location sensing and contact-tracing.
- BLE RSSI based distance estimation for social distancing.
- A CARS (Context Aware Recommendation System) based 5W-1H Recommender System architecture and an easily deployable and manipulative algorithm.

C. Novelty of the Solution Proposed in the Current Paper

Listed below are some features of the proposed system that make it stand out as a more feasible solution for social distancing and safe mobility during pandemic situations.

1) Use of SmartPhone Bluetooth Low Energy signal as a medium for distance estimation and monitoring which is inexpensive and quick to deploy.
2) Log Normal Shadow Modeling for distance estimation based on RSSI.
3) Contact information and location can also be accessed for monitoring and recommendations for safe mobility.
4) A CARS (Context Aware Recommender System) which works on code dimension tree logic for recommending safe zones for travel.

V. PROPOSED EASYBAND2.0 WORKING MECHANISM

The proposed EasyBand2.0 uses Bluetooth devices. The RSSI (Received Signal Strength Indicator) of the Bluetooth signal is used to estimate the distance of the device from a client node. The client node also enables data transfer from the Bluetooth devices upon detection. If we ignore external interference on the signal, we can still estimate the proximity of Bluetooth device in a limited space; for example, we can accurately detect if the device is present in a room or outside the room.

Green, yellow and red LED signals are used to identify, safe, mildly suspect and highly suspect users. When any uninfected user with green signal comes in close contact, i.e., in a distance less than 1.5 meters with the infected suspect, a vibrator will turn on to warn the user of the proximity. If the user continues to stay in close contact for more than 5 minutes (time assumed in the logic) a buzzer alarm will be kicked off and the green users signal will be turned to yellow, changing the status of user as 'mildly suspect'. Other users who have a green signal and who are at a distance greater than 1.5 meters away from the suspect will continue to hold the safe status, as shown in Figure 1.

A. Log Normal Shadowing Model For Distance Estimation

The most common range-based technology for distance estimation is based on RSSI measurements. This technology is used to estimate the distance of a transmitter to a receiver using the power of the received signal along with a path loss model.

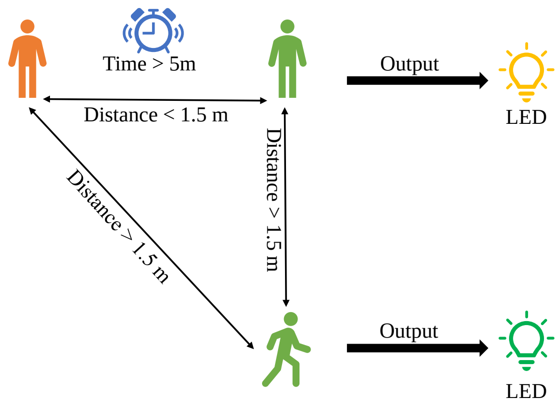

Figure 1. Working Principles of The Proposed Model.

The most commonly arising unreliable estimation due to path loss and shadowing in localization can be modeled considering the environmental variables and calibrating the path loss exponents to produce minimum error and high accuracy in the measured distance, thus making the Log Normal Shadow Model a reliable approach [11].

The expression for Log Normal Shadowing model is shown in equation 1:

$$PL(d) = PL(d_0 - 10n\log_{10}(d/d_0)) + X(\sigma), \tag{1}$$

where:

- $PL(d)$ - The received signal power loss (expressed in dBm)
- d - The distance between a transmitter and receiver
- d_0 - The reference distance, typically 1m
- $PL(d_0)$ - The path loss (expressed in dBm) at the reference distance
- n - The path loss exponent
- $X(\sigma)$ - Is a Gaussian random variable with zero mean and standard deviation σ that reflects the random variation in the path and shadow fading

In practical applications, the signal strength is affected by three factors: a) Path-loss, b) Fading, and c) Shadowing. Shadowing is the loss of signal due to obstacles between a transmitter and receiver. The path loss exponent varies for different environments, and it plays an important role in minimizing the Minimum Mean square Error (MMSE) [12].

VI. The Proposed Context Aware Recommendation Mechanism

Context Based Recommendation Systems have a wide area of applications in fields like e-commerce, e-learning, Tourism, etc. In the applications for Smart Cities, the Context Aware recommender can also be used for route recommendations for patients with certain health conditions, which also falls under the IoMT umbrella in Healthcare [13]. This system makes use of context-based algorithms to provide information specific to the user. To make the recommendations more accurate and efficient, a new recommendation has been introduced recently which is Context based and is called the Context Aware Recommendation Service (CARS). CARS considers contexts such as location, time, activity, physical conditions, social interaction, etc. to generate more accurate recommendations. For this research we are considering the following contexts:

- User- User Information is obtained from the registered users' database.
- People Near by- EasyBand2.0's sensor data will help recognize the people near by.
- Social Situation - is obtained from the news media and information released by the government.
- Location -Location information is obtained from the GPS in the user's device.
- Social Affinity - data is obtained from the media interactions and user interests derived from it.
- Safe zone - Information from the government, news media and current pandemic statistics

The proposed context aware system mainly consists of the Management Module (MM), The Context Aware Module (CAM) and the Knowledge Base. The system architecture of the Context Aware System is shown in Figure 2. The management module is responsible for user registration and profile generation. The Knowledge Base consists of databases for user data, pandemic data and the GPS data from the EasyBand2.0. The CAM module is responsible for using the data from the database and runs the given CARS algorithm and sends recommendations to the user.

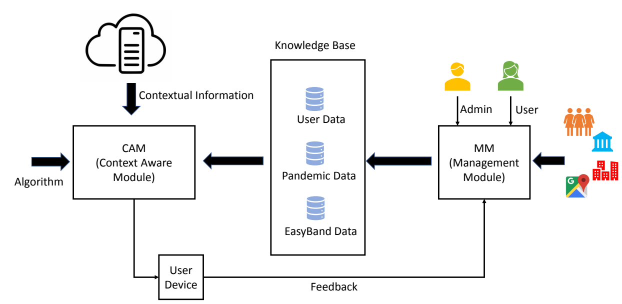

Figure 2. Context Aware System Architecture.

The CDT works on the principles of 5W-1H method in its structuring. The 5W-1H are: Location (WHERE), Role (WHO), Time (WHEN), Interest (WHAT), Utilization (WHY), and Situation (HOW). The CDT flow chart for a given user trying to navigate is as shown in Figure 3. Based on the location, the situation at the location on any given date and time the user will be recommended whether it is safe to travel or not.

VII. Implementation of 5W-1H Recommender System

The flow chart for the design flow of the 5W-1H code dimension tree is shown in Figure 3.

For the Context Knowledge Base we are using a 100K dataset from Google's Community Mobility Reports [14]. The

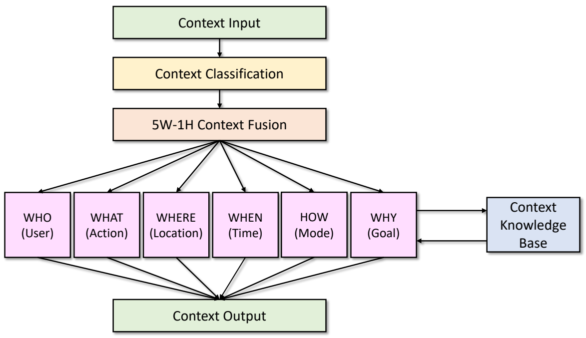

Figure 3. 5W-1H Recommender System Design.

dataset shows the mobility of people in various regions and the changes in mobility during COVID. Places considered for analysis of mobility are grocery/pharmacy, parks, transit stations, retail/recreation, residential and workplaces. Figure 4 shows the filtered data from the original dataset, showing the mobility variations at parks and recreation centers in a particular region.

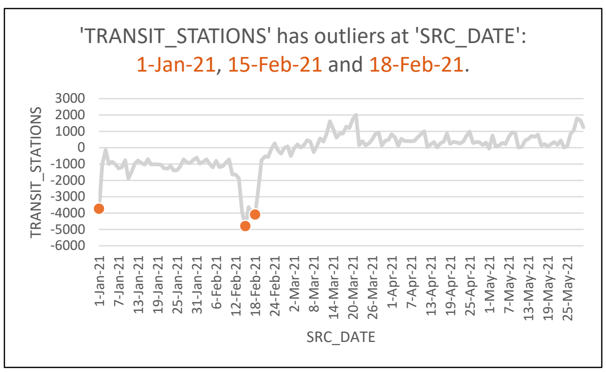

Figure 4. Chart Showing Trend in Mobility at Transit Stations.

A 23K dataset which consists of all the COVID-19 measures taken from governments across the globe is used [15]. It contains the data about various government measures enforced, including lockdowns, travel restrictions, visa restrictions, etc. These three datasets are used to form the Context Knowledge Base.

VIII. 5W-1H Algorithm

The implementation of the recommender system is divided into two logical parts, as represented in Figure 3. The first algorithm extracts the user context and queries the database to retrieve the COVID data corresponding to the given user location, time and type of request. The second algorithm makes the decision correlating the user data and the COVID data, and then outputs the suitable result as safe zone or not safe zone.

A. Algorithm-1

The first step is the execution of algorithm 1, which is a SQL query that analyzes the COVID-19 database and extracts relevant information. The COVID-19 database contains the following tables:

- $Gov\_Measures$ - Data about various government measures implemented in all regions throughout any country.
- $Covid\_Region\_Dataset$ - Mobility data of various commercial, work and recreational places.
- $Covid\_Data$ - Data of confirmed COVID-19 cases in the given location

Algorithm 1: Algorithm for Extracting Information from Context Knowledge Base

Input: Location data of user device, date, action item looked up by user
Output: Information Extracted and Exported to *.CSV file

```
Get User Location U_l, date U_l, and action item A_i
while Check== True do
    if A.Location == U_l then
        G_m=A.Measures
    else
        Output = "Data Not Found, Try Again!";
        check = False;
/* Extarcting Mobility Data from Table B */
for A_i in C and location == U_l and date == R_t do
    if A.Location==B.Location and A.date==B.date
      and C.Action==B.Action then
        M_d = B.MobilityData
    else
        Output ="Data Not Found, Try Again!";
        check = False;
/* Accessing Table D to extract Number of cases
   in the location */
while D.Location==Ul do
    C_c = D.ConfirmedCases
/* Resulting data is exported as *.CSV file for
   further Processing */
```

B. Algorithm-2

This algorithm (2) gets the User ID from the user device and verifies it with the ID stored in the database. Once the user is verified, it takes the inputs from user like date and time and the action item the user is requesting. Each action item is processed by a function which analyzes the mobility data, COVID cases data and the government measures implemented in the location. After processing all the data, a suitable message is displayed to the user. The 'Safe' message is displayed if the number of cases is low and the frequency of people visiting those places is low and no government restrictions are in place. 'Not Safe' is displayed when the positive COVID cases are high, some government restrictions are applied, or if there are no government imposed restrictions but the frequency of people visiting those places is high.

Algorithm 2: Algorithm for Context Fusion and Context Output

Input: Verifying User ID, Extracting user data like Location, Date, Time, Action Item
Output: Information Processed and Output Displayed

```
/* C++ Program which verifies the User ID and
   Calls the appropriate functions based on the
   user choice of action                          */
while Repeat==True do
    if ID==U_i then
        Output="Select From the Options";
    else
        Output="User not Identified"; Repeat = True;
    Input = UserChoice;
    Repeat = False;
while Location==U_l do
    CaseData = C_d;
    CKBdata = K_r;
/* Switch Block to call funtions based on
   UserChoice                                     */
Call the respective switch case
Each case calls the respective functions
Output message is displayed
```

IX. Experimental Validation

A. Algorithm Verification

For experimental purposes the user ID is manually entered by the user. The user name and location is retrieved from the database. Once the user is identified, a menu is displayed to select the action item. Based on the action item, algorithm 1 calls the respective function that processes the COVID-19 Data extracted by algorithm 1. A suitable message with useful information is displayed to the user, as shown in Figure 5.

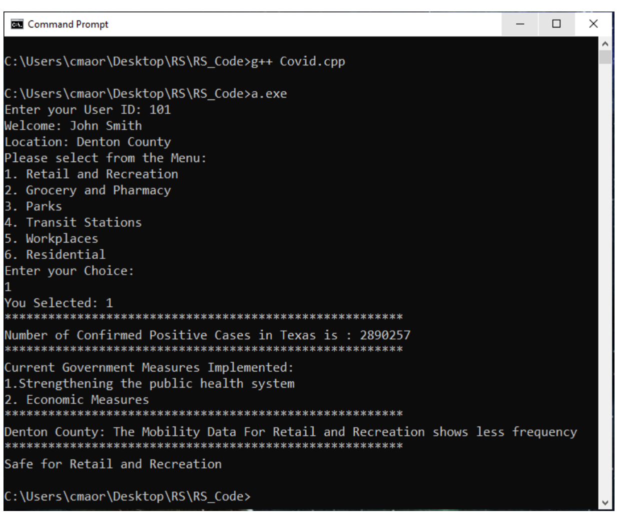

Figure 5. Output of Algorithm 2.

B. Hardware Verification and Results

The software package used for RSSI based distance estimation is BlueZ5.50. BlueZ is an open-source software and is an official Linux-based Bluetooth protocol stack initially developed by Qualcomm. In this case, the user cellphone should have its Bluetooth signal turned on, and then through `bluetoothctl` all the Bluetooth devices in the proximity are scanned. The registered devices are paired with s Raspberry Pi, and data can be transferred by using third party applications.

Table II shows the RSSI values and the estimated distance over 10 counts over a distance of 1m. The data helps to analyze the stability of the Bluetooth signal when there are no obstacles in the environment, and to set the average RSSI value measured over a distance of 1m. Based on this analysis, the environment constant is set which is a weight added to the distance to reduce the error.

Table II
RSSI Values and Distance Over 10 Counts

count	RSSI	Average Error	Distance(cm)
1	25.00	75.488	4.511
2	15.00	70.9144	13.659
3	11.00	66.094	23.544
4	5.00	55.541	56.116
5	1.00	48.833	102
6	6.00	45.958	48.415
7	6.00	43.905	48.415
8	6.00	42.365	48.415
9	5.00	40.311	56.116
10	5.00	37.324	56.116

The chart in Figure 6 shows that the error is somewhat constant at a particular distance range.

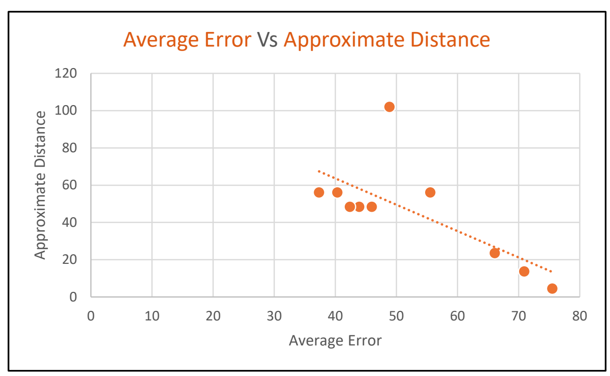

Figure 6. Error values Vs Distance.

C. EasyBand2.0 Verification

To verify the RSSI based social distancing application EasyBand2.0, the experimental setup is done using LEDs, vibrators and alarms as the output to notify the user of different proximity alerts. When the device senses another device close by, the LED lights turn on as an indication of a nearby user. There are three different LEDs: Red, Green and Yellow. Green indicates safe, Yellow is mildly-suspect and Red is highly-suspect. In this research the time spent in close proximity is tracked and the alerts are raised based on the distance, as well as time spent in proximity.

Figure 7 shows the change in status for user A when they are at a closer distance to user B.

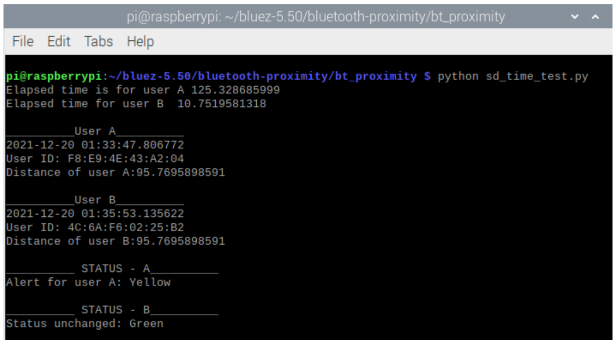

Figure 7. Code Output Showing Alert status change for User A.

The user device considered is the cellphone. The cellphone's Bluetooth is used for calculating the distance based on the RSSI. The interface is a Raspberry Pi which will generate the alerting signals based on the distance. Three different signals are shown using LEDs as shown in Figure 8. The buzzer alarm and vibrator are part of the alerting mechanism.

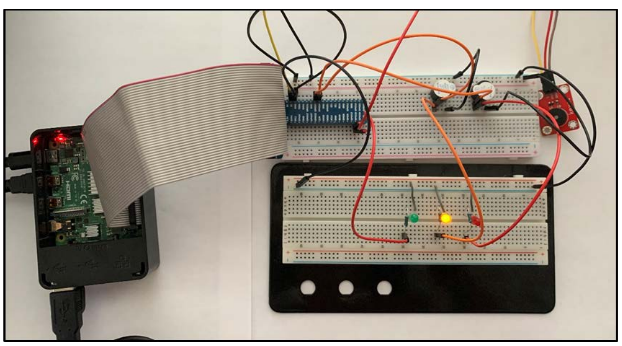

Figure 8. Hardware Implementation of EasyBand2.0.

X. Conclusions and Future Directions

BLE based social distancing and contact tracing applications are low power consuming and easily deployable options. In future the software can be quickly modified and deployed to assist in case of any other similar pandemic and the situations surrounding it. With the CARS recommendation system and the contact tracing features the application will ensure safe mobility during pandemic. The RSSI based distance estimation used in the research is sufficient for accurate distance estimation and alerting. Under the Internet-of-Medical-Things IoMT of the Smart Cities umbrella [16] the application can be modified to work as a case monitoring and reporting tool. EasyBand2.0 can effectively help in social distancing. Furthering the research towards data security and privacy there is scope towards developing an application that addresses the various attacks.

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