Towards Location Prediction for Geospatial Human Asset Tracking in COVID19 Campus Safety Bubbles

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***Abstract* — This paper provides an exploratory analysis of using contributory telemetry measurement via sensors and a user's smartphone with GPS capabilities, to aid human asset tracking within a COVID19 campus safety bubble. Our results demonstrate the usefulness to human asset tracking within these spaces. The collected experimental telemetry results about a safety bubble by location is treated as geospatial data and fed into an ArcGIS visualization dashboard to allow for campus monitoring. The paper also proposes a formal framework that supports the contributory measurement scheme evidenced by the experiments.**

***Keywords*— Geospatial, visualization, pandemic**

I. Introduction

The increasing use of ubiquitous sensor devices to help track COVID19 suspect cases has become a standard for human asset tracking within building spaces. This work looks at University campus spaces during the COVID19 pandemic and how one navigates such environments to provide some level of monitoring that guarantees against the safety bubble locations being violated. This work provides a highly relevant and important example use case for Geospatial Information Systems (GIS) research and how we can leverage this technology to implement safer re-openings of educational institutions. In this study the application is used to trigger COVID19 alerts about campus locations, and how to monitor human assets within these safety bubble locations.

By definition, the use of the term "safety bubble" in the current context suggests that the current locations across the University campus applies temperature monitoring on human assets working within these locations to ensure that body temperatures within these locations do not exceed 37 degree Celsius. If participants within the safety bubble exceed this 37 degree Celsius, the bubble can no longer be deemed safe at that point in time. As such these safety bubbles would then be sent into isolation or quarantine and screened further by the Health care providers. Only where the Health care provider gives a clearance can such safety bubbles be re-instated otherwise such safety bubbles would have be further closed until advised. We recognize that this is a first rudimentary discriminatory feature and that we have to test other features in long term because asymptomatic carriers also need to be factored in.

To identify COVID19 campus safety bubbles is a new exploration study at our local University. The authors in this work form a part of a research team that apply strong computing methods in data collection and processing via smart phones and sensors to validate threshold temperatures for these campus safety bubbles. Temperature sensors with elevated temperature values in excess of 37_0 C automatically trigger suspicion and are checked for possible COVID19 conditions. Our work does not seek to qualify at this time mis-classification or false positive studies on data self-reported from these campus safety bubbles. This is the subject of independent work where we look at Federated learning aggregators [4] that have training data sets collected from the various campus bubbles to further inform such analysis.

Arguably, to support the operations within these campus safety bubbles assumes the use of location prediction to determine where staff and students may have been honestly using these safety bubbles. It is admitted here that an honest or non-malicious user of a safety bubble would represent persons who do not exhibit elevated temperatures beyond the COVID19 normal and the ability to identify any such variations when they occur.

A post-COVID19 future will assume that these safety bubbles, albeit in a campus wide experiment as in this study or otherwise, will need to develop some type of ***contribution mechanism scheme*** or strategy that reports on user behaviour within the bubble. The first natural step into such a contribution mechanism is to look at a self-reporting or self-test evaluation mechanism for these safety bubbles. This paper underscores some preliminary experiments that capture evidence of these concerns using telemetry sensors within a controlled test environment. The most straightforward way to measure contribution from the safety bubbles is to have staff and student participants for example self-report using a score system of recorded temperatures captured while they are inside and outside the proximity of the designated safety bubbles. Although some may argue that self-reported data is not a useful contributory evaluation reporting strategy, as a first step it provides a suitable baseline that guides the intentions behind reliable tracking within these COVID19 sensitive campus locations.

Tracking malicious or suspect human behaviour that can be inferred as a violation to these COVID19 campus safety bubbles, it is important to have a set of qualifying criteria. These criteria can include (i) establishing an adversarial goal, (ii) tracking the number of offenders, (iii) looking at participant's background knowledge, (iv) looking at attack duration, (v) network reliability, and (vi) device reliability.

In terms of the adversarial goals, this assumes the scenario where participants within the safety bubble deliberately find ways to alter the ambient temperature of the environment e.g. lighting fires, changing body temperature by staying in a prolonged heat or otherwise that would lead to adverse variations in the temperature readings from the telemetry sensors that are used within the environments. Additionally, having access to modify or alter the data reported could also be a source for suspicion.

Adversarial behaviour within these safety bubbles can be carried out by individuals simultaneously, in the form of a Sybil attack [4] or persons can collude to achieve a similar adversarial goal that compromises the campus safety bubble. The simulated attacks could for example rig the sensors and/or smart phones used to collect the data and to inform the safety of these bubbles. Where there are participants within the safety bubble that have background knowledge with respect to the operations of the bubble, malicious insider attacks that change temperature settings can impact the accuracy of results at any time.

The ability to alter temperature settings within campus safety bubbles, can be sustained and go unnoticed with time. If time limits or thresholds are not established within these bubbles, as it relates to the frequency for which reports are sent to the campus administrator, managing these bubbles may become a challenge and deemed not useful. With that said, this particular concern may be the least worrying given that a COVID19 suspicion in a designated bubble for our purposes is a temperature sensitive concern reported within a timely manner such that when a participant is suspect with high or elevated body temperatures beyond the 37 degree Celsius within the bubble such participants would be removed immediately and or that safety bubble on campus would have to be closed and is treated as a time sensitive matter. We also recognize that exploration of contact tracing as soon as a candidate is identified is critical and is the focus of future work.

As we said before, we are very mindful that we cannot track asymptomatic participants that may exist within the safety bubble and this is treated as an independent concern outside the scope of this paper. The clear challenge however admittedly is minimizing or eliminating any false positives, but we treat with this latter concern as an independent research work at this time.

Network connectivity is an assumed default to reliably collect data from these safety bubbles, as the smart phones and sensors connected can only reliably send the collected data back to the campus safety bubble administrator via the ArcGIS dashboards if there is a dedicated and persistent internet connection. Similarly, device reliability emerges from the fact that our environment could comprise of faulty temperature sensors and smart phones with power battery charge problems. Thus, device error-checking, result verification, and fault tolerance are mechanisms to be examined. These are all considerations with time that can negatively affect the reliability of the data collected from our safety bubbles and that have a direct impact on the quality of the information received from the campus safety bubble network by location.

II. Proposed Framework

To manage self-reporting, via GPS mobile phones and temperature sensors, of participants within the bubble, we propose a framework that impacts the processes from data collection to data visualization; as handled as a part of the location mapping within the desired campus safety bubbles.

The basic components in our experimental use case include a smartphone, and a Bercomm temperature sensor. The smartphone provides longitude and latitude. The temperature sensor provides body temperature, room temperature, and surface temperature based on the disclosed location of our safety bubble. The pre-processing of data relating to the campus bubble locations and specifically relating to tracking the temperatures within the safety zone assumes that each participant has a Bercomm temperature sensor and that they use the sensor to periodically record the room, body, and surface temperatures within their location throughout the day. That information is collected via the smart phone and sent via a dedicated web-service to the our SQL Server [2] database system administrator, who handles the COVID19 tracking ArcGIS visualization. The collected data from the Bercomm infrared temperature sensors is currently stored as a CSV file and formatted and written to the SQL Server for persistent storage. As we expand the prototype the CSV files will only serve as a staging area to load all that CSV data to our relational SQL Server database environment or even an upgrade to Oracle12c database with a connection string from ArcGIS to query/interrogate the database as required.

As it relates to the GPS tracking capabilities of the smartphone used to map the location, we assume the principles in [3], where each location point in the intended campus safety zone bubble is described as a discrete point P, where P = {longitude, latitude, timestamp}. The trajectory of points T in the campus safety bubble could be described as $T = \{ P_1 \text{ to } P_n \}$.We extend the model in [3] to suggest that where we capture the temperature values by object within the safety bubble, such objects $O = \{ O_1 \text{ to } O_n \}$, and these objects specifically track body temperature of participants located within these safety zones. Please note that the object O can be treated as a generic data type and could also be used to track not only body temperature but room and surface area temperatures within the campus safety bubble zones for which the COVID19 suspect cases are being tracked. For now, although in our evaluation we note the surface and room temperatures within our experiments the significance of the room and surface temperatures does not impact the experimental results, and simply serve as additional meta data collected via the temperature sensors within the experimental campus safety bubble.

Since we assume that the data collected via the temperature sensors is periodic, the frequency of data collection over these sensor devices can have an impact on the device; to include things like device malfunction, battery drain, loss of power, other independent variables like loss of internet connectivity just to name a few. A particular big challenge is ensuring we can maintain unambiguous results collected from each of the discrete campus bubble locations. So for example where we have multiple temperature sensors owned by individual participants in a particular bubble yielding the same results, we have to likely treat such output values as a single record value depending on variances.

For the purpose of this work, a campus safety bubble is described as SB. In our campus world we may have several safety bubbles such that SB = {SB_1 to SB_n}. Interestingly we can liken the safety bubbles SB to grid-like networks in their own way. A safety bubble, SB, will have no less than three (3) active participants and a maximum of 20 active persons in such bubbles based on the size of the physical locations assigned to a bubble from the campus facility management unit. The guide for this number threshold is based on the adopted campus COVID19 protocols in effect. The determination of sizes of the safety bubbles is influenced by the physical space within the location, where greater space allows for a greater number of participants and the converse is true for smaller spaces and the number of participants accordingly. An audit of these campus bubble spaces was the subject of independent experiments by our research team [5].

III. PRELIMINARY EXPERIMENTS AND RESULTS

The use of temperature in this test environment is strictly for demonstration purposes and that one can apply the same techniques for other "features" that may be used to determine candidates that one suspects of having COVID-19.As a means of testing the contributory scheme of self-reporting temperature sensors of participants within a safety bubble SB, a baseline experimental study was done within an indoor / outdoor setting modelling a classroom on campus with ambient temperature readings compiled at different intervals of the day so as to observe changing temperature variations with respect to the participants SB.

The collected temperature readings were done in degrees Celsius using Bercomm infrared sensors. Readings of temperature identified three (3) student and staff participants who operated as a part of this SB safety bubble. The data collected from the Bercomm temperature sensors represent body, room, and surface temperatures about the location. These temperature values are captured and written to a CSV file as a part of the location historical data set. The CSV files serve as a staging area before we move the data to a dedicated SQL Server 2016 database environment. Sanity checks on the SQL server 2016 database is still a work in progress [2]. Each SB generates its own CSV file. In Table 1 the ambient temperature readings of the indoor and outdoor at 7:30am on January 11 2021 in the morning is collected. We note that the body temperatures of the three (3) participants in the safety bubble SB are normal as seen in Table 1 and Fig. 1 Please note that Fig. 1 is the visualized line graph of the Table 1 results. Also note that however that the surface temperatures above 37 degrees Celsius necessitates the system send out an "Orange" alert on the Bercomm temperature sensor. As the campus SB system administrator on these experiments we are not particularly concerned but any alarms for surface temperatures reported by the temperature sensors as we only treat our concerns for changes in body temperatures to make links for possible COVID19 alerts.

Table II records the body, surface and room temperatures of the safety bubble at noon where it is noticeable that the body temperatures have increased by some four (4) degree Celsius points. However, the values are still normal as the results fall below 37 degrees Celsius. Fig. 2 represents the visualized line graph of the Table II. For Table II what is noticeable though is that surface temperatures, room temperatures have climbed. The factual assertion on these latter results suggest that the ambient temperature of the environment within the proximity of the safety bubble SB has changed but nothing significant to qualify any changes in the human body temperatures that warrants any COVID19 suspicions. The higher temperatures can be attributed to the time of day the results were taken and the natural hot day of the surroundings.

TABLE I. SHOWING TEMPERATURE READINGS AT 7:30 AM 11/1/2021

Object/place	*Temperature*	*Time*
Person 1	32.2	7:30 AM
Person 2	32.2	7:30 AM
Person 3	32.2	7:30 AM
Surface 1	30.1	7:30 AM
Surface 2	39.4	7:30 AM
Surface 3	30.1	7:30 AM
Room	32.2	7:30 AM
Outside (sun)	32.1	7:30 AM
Outside (shade)	30.1	7:30 AM

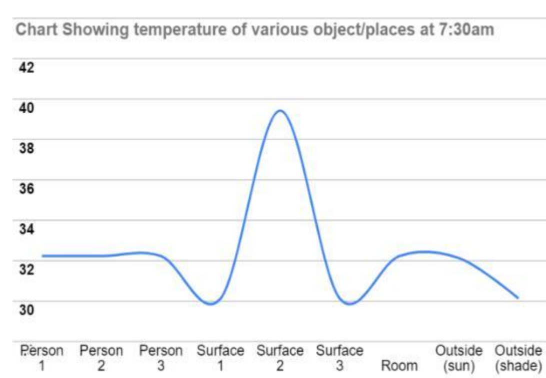

Fig. 1. Chart showing temperature readings at 7:30 am January 11 2021

Table III highlights from the noon experiments recorded in Table II, that two Bercomm temperature sensors were used and labelled Gun# 1 and Gun #2. The two temperature sensors were used to interrogate any possible variances in the recorded body, surface and within the same safety bubble. Fig. 3 and Fig. 4 visualize the Table III results. We note that the variances of the results from the two temperature sensors (Gun# 1 and Gun#2) are less than 1% , which allows us to confirm our earlier suppositions of argument that we could in fact ignore any differences if the participants in the same safety bubble had more than one sensor tracking the environment. The vertical rise in the line graphs between Fig. 1 and Fig. 2, simply evidences the changes in the ambient surface temperature, inside and outside the safety bubble proximity.

TABLE II. SHOWING THE TEMPERATURE READINGS AT 12 NOON 11/01/2021

Object/place	*Temperature*	*Time*
Person 1	36.1	12:00 PM
Person 2	36.1	12:00 PM
Person 3	36.9	12:00 PM
Surface 1	37.1	12:00 PM
Surface 2	60	12:00 PM
Surface 3	39.4	12:00 PM
Room	32.1	12:00 PM
Outside (sun)	36.8	12:00 PM
Outside (shade)	32.2	12:00 PM

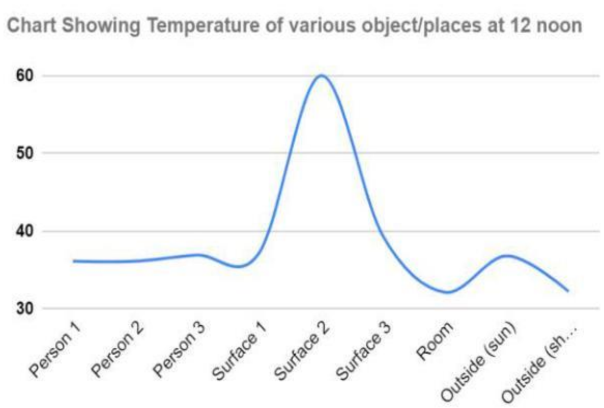

Fig. 2. Chart showing temperature readings at 12 noon

Green caution codes from the sensors represent a normal situation.

TABLE III. SHOWING THE TEMPERATURE TAKEN BY DIFFERENT TEMPERATURE GUNS

	Gun #1	*Gun #2*
Object	*Temperature*	*Temperature*
Person 1	36.1	36.3
Person 2	36.2	36.2
Person 3	36.3	36.1
Person 4	37.1	36.9
Surface #1	39.5	40.1
Surface #2	60	60
Room #1	32.1	32.2
Room #2	32.5	32.5
Outside(sun)	37.5	37.5
Outside(shade)	32.2	32.3

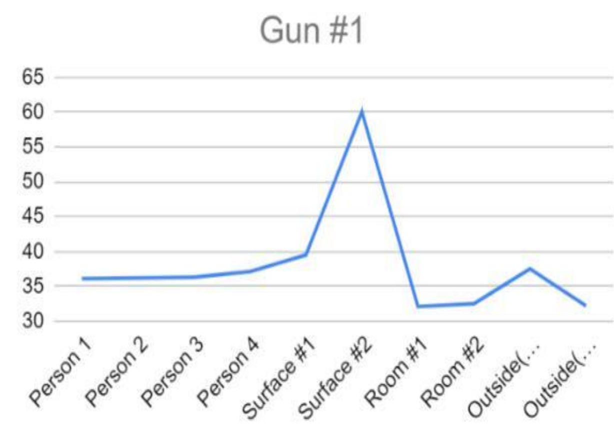

Fig.3. Chart showing temperature readings from temperature gun 1

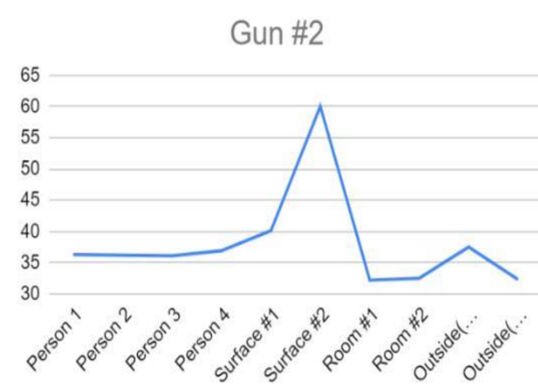

Fig.4. Chart showing temperature readings from temperature gun 2

Table IV provides the temperature caution codes for when body and surface level temperatures are normal and/or abnormal. A caution code of Orange and Red assumes that the ambient temperatures exceed the 37 degree Celsius within the safety bubble. Where the body temperatures exceed 37 degrees such that you have a caution code of Orange or Red needs to be urgently reported as those concerns could in fact be a suspect COVID19 concern.

Bercomm Temperature gun			
Mode	***Range***		
		Min	*Max*
Body Mode			
	Lo	0	32
	Green	32	37.3
	Orange	37.3	37.9
	Red	38	42.9
Surface Temp		0	60
Room		0	40

TABLE IV. SHOWING THE TEMPERATURE RANGE OF THE TEMPERATURE GUN BASED ON THE SET MODE

IV. Conclusion

This paper provided an exploratory analysis of using contributory telemetry measurement via sensors and a user's smartphone with GPS capabilities to aid human asset tracking within a COVID19 University campus safety bubble. Our results demonstrate the usefulness to human asset tracking within these spaces as system administrators for configuring and simulating campus test safety bubble environments. The work provided a basic framework along with associated experiments for handling the data collection and processing that is used by for informing our ArcGIS Geospatial visualization dashboard. Our work represents the first of its kind as far as we see in the literature.

Based on the empirical evaluations and observations, our next step is to model a large scale deployment of safety bubbles with their own discrete location points, and then build suitable classification and machine learning model using Federated learning aggregators for tracking anomalous temperature changes within the different safety bubbles and reporting this via our Geospatial data visualization boards. Considering that these safety bubbles are in several physical locations across campus, with larger numbers of participant tracking needs a federated learning service implementation and testing at scale of these implementations would be very useful as we seek to deliver on the expectations of our University COVID19 task force who are anxious to understand the further benefits of our approach.

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