On the Performance of Automatic Exposure Determination Using Bluetooth-based Proximity Estimation

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***Abstract*— The proximity detection mechanism in current automatic exposure notification systems is typically based on the Bluetooth signal strength from the individual's mobile phone. However, there is an underlying error in this proximity detection methodology that could result in wrong exposure decisions i.e., false negatives and false positives. A false negative error happens if a truly exposed individual is mistakenly identified as not exposed. This misidentification could result in further spread of the virus by the exposed (yet undetected) individual. Likewise, when a non-exposed individual is incorrectly identified as exposed, a false positive error occurs. This could lead to unnecessary quarantine of the individual; and therefore, incurring further economic cost. In this paper, using a simulation platform and a notion of proximity detection error, we investigate the performance of the system in terms of false exposure determinations. Knowledge of how the Bluetooth-based proximity detection error impacts such false determinations and identification of methodologies that can reduce this impact will be helpful to enhance the effectiveness of an automatic contact tracing system. Our preliminary results indicate the substantial impact of the proximity estimation error on the exposure detection accuracy. The results also suggest how proper filtering of distance measurements may reduce this impact.**

Keywords- Proximity Detection, Bluetooth, Exposure Notification, COVID-19, Contact Tracing

I. INTRODUCTION

Contact tracing is an epidemiological technique used to identify people who have had "contact" with an infected person. The Centers for Disease Control and Prevention (CDC) defines a "contact" as anyone who has been within 2 meters of the infected person for at least 15 minutes, beginning 2 days prior to the appearance of his symptoms, and lasting until he was isolated [1]. Prior to COVID-19, contact tracing was primarily a manual process where people who were in close proximity to a known infected person are traced and identified. Once those contacts are identified, public health workers will notify them of a potential exposure and provide instructions to help prevent further spread of the disease. The instructions typically involve a period of self-isolation (i.e., quarantine).

Automatic Exposure Notification is an electronic notification protocol based on a proximity detection mechanism such as Bluetooth Low Energy (BLE) ranging and privacy preserving cryptography. Widespread usage of smart phones among the population and the availability of BLE technology in those phones have prompted governments and industry to also consider automatic exposure notification to combat the spread of the virus during a pandemic. Usage of this protocol involves installing an app developed and published by authorized health authorities. Although the effectiveness of automatic exposure notification relies on adoption and utilization of this app by a vast number of people in a community, it can potentially offer many advantages over the traditional manual contact tracing. For example, it is clearly a faster approach to notify possibly exposed individuals compared to manual tracing. In pandemic situations, time is of an essence and any delay in identifying potentially exposed people could have major consequences. The automatic notification is also conducted in a private manner, giving the exposed person the control on how to proceed or engage with the public health officials. The protocol can also discover individuals who are not necessarily known to the infected person. Such individuals might be hard to locate or identify using the traditional manual tracing [2].

Automated exposure notification can effectively complement or assist manual contact tracing process specially during pandemics when there are limited resources available. The ultimate goal of contact tracing is to accurately notify the right people (i.e., people who were truly exposed) to quarantine in a timely manner and let other individuals who were not exposed to function in the community as usual. In this way, not only the spread of the virus is better controlled but also the negative economic impacts of general public lockdowns are avoided or minimized.

BLE signal measurement is the most popular mechanism for proximity detection in an automated exposure notification system. Location-based technologies such as GPS or QR code scanning have also been suggested as a mean to estimate proximity; however, privacy concerns, spatial resolution/accuracy and other practical limitations often create challenges to their effective implementation and public adoption. The Private Automated Contact Tracing (PACT) project led by several laboratories at MIT has developed one of the most widely used apps that can be installed on most commercially available smart phones [3]. The app uses the BLE signal strength to estimate proximity of two individuals holding the phones. These distances are used to assess whether sufficient contact with an infected individual has been made before an exposure notification is sent to the healthy individual.

In all BLE-based proximity detection mechanisms, there is an underlying error in the process that converts the signal strength into distance. This error is due to the variations in propagation of the Bluetooth signal. The variations are caused by many factors such as the surrounding environments, phones positions and orientations relative to the individuals carrying them, antenna gain patterns of the phones, etc. The accumulative effect of the error in the estimated distances could lead to wrong decisions in the exposure determination i.e., false negatives and false positives. A false negative error occurs when an exposed individual is incorrectly identified as not exposed. Similarly, a false positive error occurs when a non-exposed individual is mistakenly identified as exposed. Both types of errors have costly implications; and can ultimately determine the effectiveness of the Bluetooth-based automatic contact tracing in containment of pandemics such as COVID-19. To the best of the authors' knowledge, there are no prior studies that investigated the impact of this underlying error on the binary exposure decision (i.e., exposed/not exposed). In this paper, we present a platform that allows for the analysis of the system performance under various parameters. This platform enables us to gain a better understanding on how the underlying technology error propagates through the contact tracing system. Preliminary results show the considerable impact of the Bluetooth-based proximity estimation error on false exposure determination. We also present preliminary results on how proper filtering of the estimated proximities could significantly reduce the resulting false exposure determinations.

The rest of the paper is organized as follows. Section II presents the statistical model of the error in the estimated distance using Bluetooth between two individuals carrying mobile phones. Section III describes the simulation platform that has been developed to study potential exposures using BLE-based proximity detection. Preliminary simulation results and analysis are provided in Section IV. Finally, conclusions and plans for future work are described in Section V.

II. Probability Distribution of Error in the Estimated Distance

Typical exposure notification in automatic contact tracing is based on Bluetooth signal measurement between two mobile phones. The Bluetooth signal is used to estimate the distance (or proximity) between the two people carrying the phones. Knowing this proximity and its duration, the CDC guidelines [1] are then used to determine the possibility of exposure to an infected individual carrying a virus such as COVID-19. The main concept behind Bluetooth-based proximity detection is the relationship between the Received Signal Strength (RSS) from a Bluetooth transmitter and the travelled distance of the Bluetooth signal before reaching the receiver. In ideal scenarios when there are no objects around (including the people holding the phones) and ideal isotropic antennas, the RSS is inversely proportional to the square of the distance between a pair of Bluetooth transceivers. However, in practice, the reflections, scattering and shadowing caused by the objects in the surrounding environment will lead to random fluctuations of the received signal. In addition to the environment, the bodies of the people carrying the phones as well as exact position and orientations of the phones will impact the signal transmission path and therefore the RSS. These random fluctuations in RSS will impact the accuracy of the estimated distance between the two mobile phones which consequently result in false positive or negative identifications in an automatic exposure notification system. Therefore, it is important to understand how this inherent error in the estimated distance leads to such potential misidentifications.

In this Section, we present a methodology to obtain a statistical model for the error in the estimated distance from a pathloss model between two Bluetooth transceivers. To the best of our knowledge, there are currently no statistical channel models in the literature that represent Bluetooth signal pathloss between two mobile phones carried by two individuals in various environments. However, in [4, 5, 6], it has been shown that the pathloss model for a personal area network using BLE has similar characteristics (i.e., loss exponent and shadowing variances) to a wireless local area network (WLAN) operating at the same frequency band. Therefore, here we start our derivation by considering a Lognormal pathloss distribution for the Bluetooth channel along with a Gaussian distributed shadowing and fading component X_σ. It should be emphasized that once a more customized pathloss model for the BLE channel between two mobile phones is available, a similar methodology can be followed to extract the statistical model of the estimated distance between those phones. For now, we assume that the BLE channel pathloss at distance d (i.e., $PL(d)$) can be expressed as follows:

$$PL(d) = PL(d_{ref}) + 10n \, log\left(\frac{d}{d_{ref}}\right) + X_\sigma \tag{1}$$

where

$$f_{X_\sigma}(x) = \frac{1}{\sqrt{2\pi}\,\sigma} e^{-\frac{x^2}{2\sigma^2}} \qquad -\infty < x < \infty$$

d_{ref} is a reference distance with a known pathloss, n is the pathloss exponent, and X_σ is a random variable representing the impact of the shadowing, fading and scattering on the wireless signal from the surrounding environment. The probability distribution associated with X_σ (i.e., $f_{X_\sigma}(x)$) models the variation in the pathloss at a given distance d. However, it can also be used to derive a statistical model for the variations in the estimated distance for a given $PL(d)$. Assuming a fixed transmit power, variations in $PL(d)$ is equivalent to variations in RSS. Therefore, a mathematical model describing the error in the estimated distance can be obtained as follows.

Consider d and d_0 to be the estimated and true distances between a transmitter and a receiver. Then, from equation (1), we can get:

$$d = d_0 10^{-\frac{X_\sigma}{10n}} \tag{2}$$

Error in the estimated distance can be defined as: $Y = d - d_0$; therefore, random variable Y can be expressed by:

$$Y = g(X_\sigma) = d_0(10^{-\frac{X_\sigma}{10n}} - 1) \tag{3}$$

Suppose $f_Y(y)$ and $f_{X_\sigma}(x)$ represent the probability density functions of the random variables Y and X_σ respectively, then:

$$f_Y(y) = \frac{f_{X_\sigma}\left(g^{-1}(Y)\right)}{g'[g^{-1}(y)]} \tag{4}$$

Using the Gaussian distribution associated to the random variable X_σ and equations (3) and (4), we can obtain the following probability density function for the error in the estimated distance.

$$f_Y(y) = \frac{1}{\sqrt{2n}} \frac{10n}{\sigma\, log_e(10)} \frac{1}{(d_0 + y)} e^{-\frac{1}{2}\left(\frac{10n}{\sigma\, log_e(10)}\right)^2 \left(log\left(\frac{Y}{d_0}+1\right)\right)^2} \tag{5}$$

Some of the steps in the derivation of the above distribution have been omitted for brevity. As observed, this probability density function depends on the pathloss exponent n , standard deviation of the fading σ , as well as the true distance d_0. The pathloss exponent n depends on the environment where the Bluetooth transceivers are communicating. For our analysis in the next section, we have assumed a pathloss exponent of $n = 2$. Standard deviation of the fading (σ) heavily depends on the propagation channel. This is the main parameter that impacts the accuracy of the proximity detection in a BLE-based automatic exposure notification. Fig. 1 shows the probability distribution of the estimated error when $d_0 = 4$ meters, $n = 2$, and $\sigma = 1, 2, 3, 4, 5$. Although a distance of four meters is clearly outside the exposure threshold, as σ increases, there will be an increasing likelihood that the error in the BLE proximity mechanism could push the estimated distance below the 2 meters radius. Therefore, a person who is clearly outside the exposure distance limit could be assumed to be too close to an infected person.

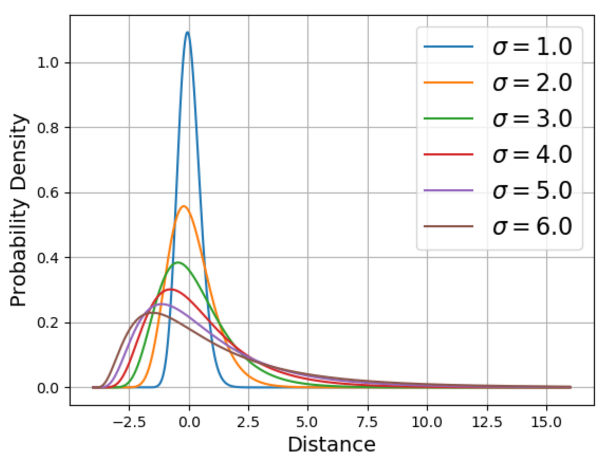

Fig. 1: Sample probability distribution of the error in the estimated distance at $d_0 = 4$

III. SIMULATION PLATFORM

In order to understand the effect of the Bluetooth proximity estimation error on automatic exposure notification, a simulation platform has been developed to test scenarios involving people walking in a plaza, campus area, or neighborhood. Initially, a population of agents is created and randomly placed within a closed simulation area. A certain percentage of the population is designated as being infected and contagious. The mobility pattern of the agents will obviously play an important role on the exposure possibilities. Mobility patterns that allow gatherings of a variable size groups of individuals with variable conversation length are also being added to this simulation platform. In this paper, we used the mobility algorithms in [7] to conduct our initial study. The algorithms allow us to select and modify both the individual parameters of each agent's behavior (affecting its speed and movement) as well as the goals that each agent is working towards. A potential difficulty with dynamic approaches in agent mobility algorithms is the possibility of jamming [8]. Jamming can occur when all the agents in a simulation have similar goals, e.g., all trying to reach the same area within the simulation field. To avoid jamming and thus biasing the results in our simulations, we periodically randomize the goals of each agent. Using this platform, we track the true and estimated distances between any two moving agents at fixed time intervals. Here, we have chosen one second as the length of this time interval. The estimated distance is calculated as the summation of the true distance and an error which is due to the BLE proximity detection mechanism. The statistical distribution of this error was obtained in the previous section and shown in equation (5).

Each healthy agent in the simulation maintains two counters: (a) True Exposure Counter (TEC), and (b) Estimated Exposure Counter (EEC). The true exposure counter keeps track of the total time when the true distance from infected agents has been below 2 meters. Likewise, the estimated exposure counter shows the total time when the estimated distance from infected agents has been below 2 meters. The true and estimated exposure counters are updated every second after incorporating the population dynamics in the simulation platform. The counters are used to make exposure determination for all healthy agents at any time during the length of a simulation. Comparison of the values of these counters to the 15 minutes threshold set by the CDC guidelines will lead to 4 possible states for each agent including two types of errors in exposure determination.

A false positive exposure error occurs when the true distance counter of a heathy agent is less than 15 minutes while its estimated exposure counter is above 15 minutes. Conversely, a false negative exposure error occurs when the agent's true distance counter goes above the 15 minutes threshold while the estimated distance counter shows the accumulated exposure time still below that threshold. The state diagram shown in Fig. 2 describes possible states for an agent and conditions for transitioning among them within the simulation platform.

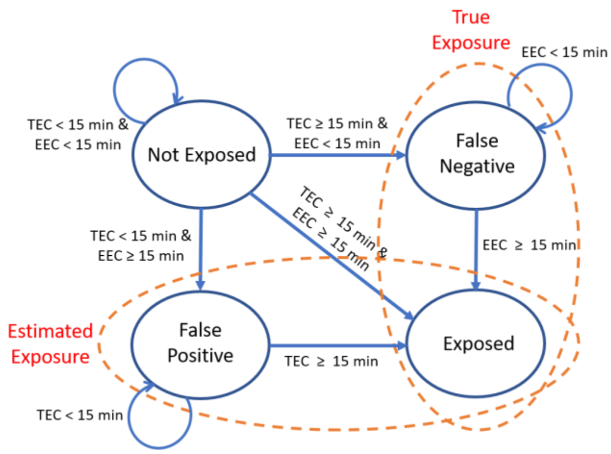

Fig. 2: State diagram of the agents in the simulation platform

To reduce the number of exposure checks at each time interval, we assume a cutoff radius of 10 m around any infected/contagious agent in the simulation. This 10 m radius is typically considered to be the maximum range of a BLE signal in favorable environments [9]. Even if the Bluetooth signal of the infected agent's mobile phone can reach beyond the 10 m radius, we can show that the probability of estimated exposure will be very insignificant. This can be observed by plotting the term $\Pr(d \leq 2 \mid d_0)$ using equation (2) (i.e., the conditional probability of the estimated distance to be less than 2 meters when the actual distance between two agents is d_0). This probability for various values of σ is shown in Fig. 3. As observed, there is negligible probability of exposure when the separation between two agents is beyond 10 m (i.e., $d_0 \geq 10$).

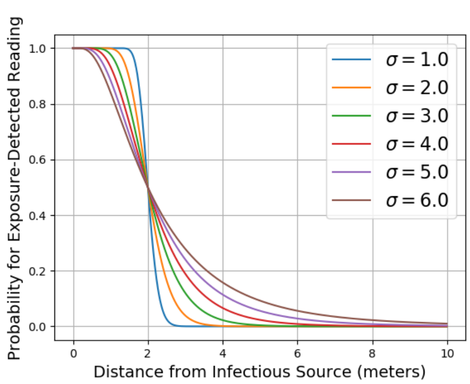

Fig. 3: Exposure probability for various values of d_0

IV. Simulation Results and Discussion

As stated in Section II and observed in Fig. 1, the probability distribution of the error in the estimated distance is a function of the true distance (d_0), standard deviation of the shadowing/fading (σ) and pathloss exponent (n). Assuming a fixed pathloss exponent of $n = 2$, extensive simulations have been done using the platform discussed in the previous section to investigate the impact of σ on false exposure determination. Fig. 4 shows the maximum average numbers of false negatives/positives with the corresponding confidence interval of one standard deviation versus σ. The confidence interval of one standard deviation is also used for other results in this paper. The results presented in this paper consider a population of 135 agents moving within an area of size 162 m x 35 m for 8 hours (i.e., typical length of a workday). These numbers are chosen based on a standard laboratory building inside the campus area of the National Institute of Standards & Technology where the authors work.

The number of infected individuals at the beginning of the simulation is set to 5% of the population. As observed, false positive counts noticeably increase as σ increases. With $\sigma = 5$ and during 8 hours of simulation, almost a quarter of the population will be erroneously identified as "exposed" (i.e., false positives). This implies that a significant percentage of the population could be required to go to quarantine in addition to the detected exposed people. The mobility pattern used in these simulations considers agents that are constantly moving. This leads to higher probability of agents being outside the 2 m radius of each other than inside. Agents that are outside the 2 m radius can only result in false positive type of erroneous exposure determination. Therefore, higher error intensity (i.e., σ) will increase the likelihood of agents that are farther away from an infected agent to be mistakenly estimated within the 2 m radius. This is why there is a significant rise in the number of false positives with increasing σ. Similar trends in the results are also observed with lower percentages of infected agents at the beginning of the simulation; however, longer interactions between the agents (e.g., multiple days) might be needed.

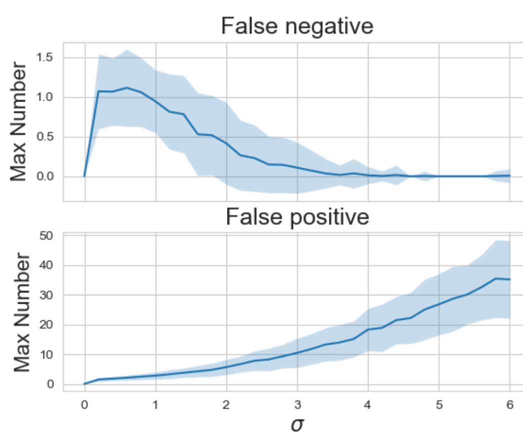

Fig. 4: Number of false exposure determinations versus σ

Although there is a monotonic increase in the number of false positives, the number of false negatives on the other hand slightly increases at first and then decreases as σ increases. This may seem counter-intuitive but the reason behind this trend is the rapid increase in the number of false positives within the population. A false negative can only occur when an agent is within the 2 m radius of one or more infected agents for over 15 minutes but the error in proximity detection causes the EEC to fail to register this time beyond the 15 min threshold. The higher error intensity σ should normally increase the likelihood of this event; however, with the quick rise in the number of false positives, the remaining pool of potentially "not exposed" agents that could fall within the 2 m radius will decrease rapidly. This in turn results in less probability of transition from the "not exposed" state to the "false negative" state" (see Fig. 2) as σ increases further. If there were no possibility of false positives in the system, then we could expect a monotonic rise in the number of false negatives as well. This can be easily verified by setting the sensing radius of the BLE signal to 2 m instead of the 10 m that was used to obtain the results in Fig. 4. With that setting, only false negative exposure detections can occur. Fig. 5 shows the change in the number of false negatives versus σ when there are no false positives (i.e., sensing radius = 2 m).

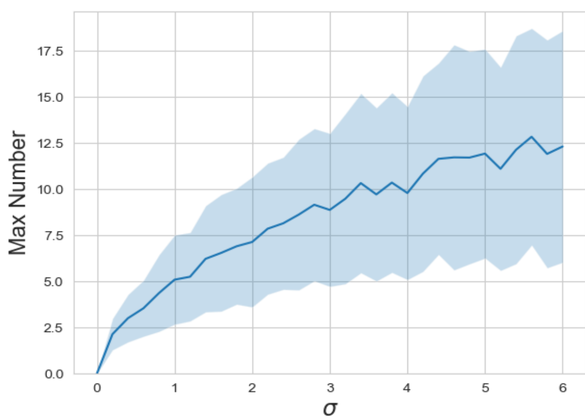

Fig. 5: Number of false negatives versus σ

The results in Figs. 4 and 5 have been obtained when the instantaneous values of the estimated proximities are used in the TEC and EEC calculations. The sequence of these instantaneous samples is most likely correlated in time and does not constitute an independent and identically distributed process. This is because the error samples are related to the variation of the received signal strength when the individuals holding the phone move around. Knowledge of the temporal correlation of the BLE wireless channel can potentially be used to determine the correlation between the error samples in the estimated proximities. In practice, a filter (i.e., windowing function) can be used to exploit this correlation and smooth the estimated distances in order to reduce the impact of σ. For two stationary agents a simple rectangular window can asymptotically reduce the error to zero when the length of the window is increased. It is conjectured that the optimal length of this window for non-stationary agents depends on the coherence time of the BLE channel which in turn relates to the mobility pattern of the population under study.

For the mobility algorithms used in our platform, we have observed that a simple 3-point moving-average window will significantly reduce the total number of false exposure determinations. These results are shown in Fig. 6. Although the number of false negatives has relatively increased to an average maximum of around 3, the number of false positives has dropped significantly. The impact of windowing can also be observed by looking at the average total number of false exposure determinations (i.e., false positives + false negatives) versus time during the 8 hours simulation. Fig. 7 shows this impact for $\sigma = 2$.

Fig. 6: Number of false negative and positive determinations versus σ after applying 3-point moving average

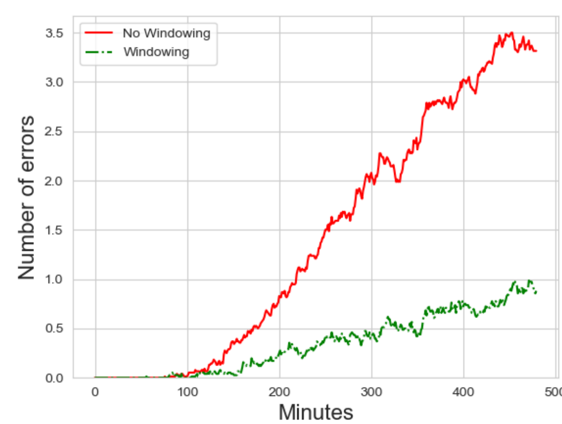

Fig. 7: Number of false exposure determinations during 8 hours of simulation ($\sigma = 2$)

V. Conclusions and Future Work

This paper reports our initial results on the effect of the underlying error in Bluetooth proximity estimation on the accuracy of the exposure decisions in an automatic contact tracing system. Since analytical investigation of this problem is not feasible, we have developed an agent-based simulation platform which allows for evaluation of a wide range of scenarios with a large number of agents. Our preliminary results indicate that the proximity estimation error using BLE may have substantive effect on the number of false exposure determinations. False negative determinations adversely impact infection propagation while false positive determinations incur economic cost due to the increase in the number of unnecessary quarantines. Therefore, it is important to develop strategies that can minimize these errors by considering their trade-offs and corresponding risks.

We plan to extend the simulation platform by incorporating additional mobility patterns for the agents (e.g., patterns involving congregation) and investigate the effect of each pattern on the resulting false exposure determinations. A deeper study of the windowing function and its potential relationship to the dynamics of the agents' movement (e.g., speed) might also be beneficial to minimize the impact of σ on false determinations. The frequency of BLE signal measurement will also make an impact on the accuracy of the estimated proximity. This is especially important for scenarios where people are constantly moving. Although higher measurement frequency could potentially lead to higher accuracy in the estimated distance, it will drain the battery of the mobile phone and could necessitate more frequent recharge when a contact tracing app is installed. The impact of the length of the time interval between consecutive BLE signal measurements will be studied using our platform in continuation of this project.

Aside from the BLE-based distance estimation, our agent-based simulation platform also offers the flexibility to evaluate other proximity detection mechanisms. Any methodology with a corresponding probability distribution for the error in the estimated distance can be easily integrated in our simulation platform and analyzed for its impact on the resulting false exposure determination. In general, the platform can also be extended to statistical exposure models that are based on the potential relationship between the received signal strength and viral load. Such models can more appropriately link the received signal strength directly to the exposed amount of the viral particles (i.e., droplets and aerosols) [10]. As a result, the hard 2 meter/15 min threshold could be replaced by a soft distance/exposure time criterion.

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