Evaluation of the Bluetooth-based Proximity Estimation for Automatic Exposure Determination

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Abstract— **A commonly used methodology to estimate the proximity of two individuals in an automatic exposure notification system uses the signal strength of the Bluetooth signal from their mobile phones. However, there is an underlying error in Bluetooth-based proximity detection that can result in wrong exposure decisions. A wrong decision in the exposure determination leads to two types of errors: false negatives and false positives. A false negative occurs when an exposed individual is incorrectly identified as not exposed. Similarly, a false positive occurs when a non-exposed individual is mistakenly identified as exposed. Both errors have costly implications and can ultimately determine the effectiveness of Bluetooth-based automatic exposure notification in containment of pandemics such as COVID-19. 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. Alternatively, using this platform, analysis can be performed to determine the acceptable accuracy level of a proximity detection mechanism in order to have a more effective contact tracing solution.**

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. In the United States and for COVID-19, the Centers for Disease Control and Prevention (CDC) defines a "contact" as anyone who has been within 2 meters of an infected person for at least 15 minutes, beginning 2 days prior to the appearance of his/her symptoms [1]. Prior to COVID-19, contact tracing was primarily a manual process to trace and identify people who were in close proximity to a known infected person. Once those people are identified, public officials will notify them of potential exposures along with instructions to prevent further spread of the disease. The procedure after such exposures typically involves a period of self-isolation and may also include testing.

Automatic Exposure Notification is an electronic notification protocol based on a proximity detection mechanism such as Bluetooth Low Energy (BLE). These protocols often include various privacy preserving mechanisms to protect the privacy of the users. The popularity of smart phones and the availability of BLE technology in the new generation of these phones make automatic exposure notification a viable approach to slow down or prevent the spread of the virus during a pandemic. This approach requires installing an app developed and published by authorized health authorities. The effectiveness of automatic exposure notification critically depends on the adoption and utilization of this app by an overwhelming majority of people in a community. The cost and practical advantages of automatic exposure notification over the traditional manual contact tracing justifies its adoption and usage. One of these advantages is a faster notification of the exposed individuals compared to manual tracing. In pandemic situations, time is of an essence and any delay in identifying exposed people could have major consequences. Another advantage is that by using automatic exposure notification individuals who are not necessarily known to the infected person can easily be identified. Such individuals might be hard to locate using the traditional manual tracing [2].

Automated exposure notification can effectively complement or assist manual contact tracing process during pandemics, especially when resources for manual contact tracing is not sufficient. The combination of automated exposure notification and manual contact tracing along with appropriate policy decisions is expected to efficiently contain the spread of the virus at minimal economic cost. The accuracy of exposure determinations directly impact the success of this containment. Location-based technologies such as GPS or QR code scanning have also been suggested as a means to estimate proximity in contact tracing systems. However, privacy concerns, spatial accuracy, and other practical limitations have created challenges to their implementation and public adoption. As such, BLE signal strength measurement is the most popular mechanism for proximity detection in an automated exposure notification system. 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]. This app uses the BLE signal strength to estimate the distance between two individuals holding the phones. These distances are used to assess whether the contact with an infected individual justifies sending exposure notification to the healthy individual [4].

The accuracy of BLE-based proximity detection heavily depends on the mapping from the BLE received signal strength to the corresponding distance between the two individuals. The variations in the Bluetooth signal propagation will cause an unavoidable error in this mapping. These variations are due to many factors such as the surrounding environments, phones positions and orientations relative to the body, antenna gain patterns, etc. Inaccuracies in the estimated distances can lead to wrong exposure determinations such as 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 wrongly identified as exposed. Both types of errors have costly implications and can ultimately reduce 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 have investigated the impact of this underlying error on the binary exposure decision (i.e., exposed/not exposed). In this paper, a simulation platform is presented that allows for the evaluation of the system performance under various parameters. One of the objectives of this platform is to gain a better understanding on how the underlying BLE technology error affects the effectiveness of the contact tracing system. Our preliminary results demonstrate that inaccuracies in the Bluetooth-based proximity estimation may result in high rate of false exposure determination. In addition, it is shown that proper filtering of the estimated proximities may substantially reduce the rate of such false determinations.

The rest of the paper is organized as follows. Section II describes the simulation platform that has been developed to study potential exposures using BLE-based proximity detection. Preliminary simulation results and discussions are provided in Section III. Finally, conclusions and plans for future work are described in Section IV.

II. Simulation Platform

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. To conduct our initial study, here we have used the mobility algorithms in [5]. The algorithms enable us to choose and modify the individual parameters of each agent's behavior (e.g., speed and movement) as well as the agents' goals. A potential challenge with agent dynamic in mobility algorithms is the possibility of jamming [6]. 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 prevent jamming and the potential of biasing of the results, the goal of each agent is periodically randomized during each simulation. Using our platform, the true and estimated distances between any two moving agents can be tracked 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 can be obtained from a given pathloss distribution associated with the Bluetooth wireless channel.

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. Similarly, the estimated exposure counter keeps track of the total time when the estimated distance from infected agents has been below 2 meters. These counters are updated every second after considering the population dynamics in the simulation platform. Exposure determination for all healthy agents can be made based on these counters at any time during the length of a simulation. Comparison of the values of these counters to the CDC guidelines (i.e., 15 minutes threshold) leads to 4 possible states for each agent including two types of errors in exposure determination.

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. Conversely, 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. A cutoff radius of 10 m around any infected agent has been considered in the simulation to limit the number of exposures checks at each time interval. This radius is often considered as the maximum coverage of a BLE transmitter in environments which cause minimal multipath and shadowing on the signal propagation path [7]. Also, it can be shown that the probability of estimated exposure will be insignificant if the Bluetooth signal of the infected agent's mobile phone can reach beyond the 10 m.

III. Simulation Results

Consider a population of 800 agents moving according to the mobility model [5] inside a 100 m x 100 m area. The number of infected agents at the start of the simulation is set to 5% of the population. Duration of the simulation is set to 8 hours to represent one full working day. Assuming a Lognormal pathloss distribution for the BLE channel with a Gaussian distributed shadowing and fading component with standard deviation σ, the distribution of the error in the estimated distance would be a function of (σ), pathloss exponent (n) and the true distance between the agents. For a pathloss exponent of $n = 2$, the impact of error in the estimated distance on false exposure determination can be investigated using the simulation platform described in the previous section. Figure 1 shows the maximum average numbers of false negatives and positives versus σ for the scenario described above. The confidence interval of one standard deviation has been used for all results presented here. As observed, when $\sigma = 0$, there is no error in the estimated distance, and therefore, there are no false exposure determination in the system. However, as σ increases, number of false positives noticeably increase as well. In environments with strong fading and shadowing (e.g., $\sigma = 5$), almost half of the population will be mistakenly identified as "exposed" by the end of the simulation. As a result of this misidentification, a significant percentage of the population could be asked to quarantine. These are in addition to the detected exposed people who also require isolation.

The mobility pattern used in these simulations does not consider occasional congregation by the agents. The constant movements of the agents lead to higher probability of their true distances being over the 2 m radius of each other. For agents that are outside the 2 m radius of an infected agent, error in proximity detection can only result in false positive type of exposure determination. In addition, higher error intensity (i.e., σ) will increase the likelihood of this false positive determination. This is the main reason for the significant rise in the number of false positives with increasing σ in Fig. 1.

Fig. 1: Number of false exposure determinations versus σ

Despite the monotonic increase in the number of false positives, the number of false negatives slightly increases at first and then decreases as σ increases. The main reason behind this trend is the rapid increase in the number of false positives within the population. A false negative occurs when an agent is within the 2 m distance of another infected agent for over 15 minutes; however, the error in the estimated proximity leads to the failure by the EEC to correctly capture this time above the 15 min threshold. Normally, higher error intensities (σ) increases the likelihood of this event; but here, with the rapid increase in the number of false positives, the remaining "not exposed" candidates that could fall within the 2 m radius of an infected agent will decrease quickly. This means that on average, there will be a smaller number of "not exposed" agents that can be mistakenly determined as "false negative" when σ increases. If there were no possibility of false positives, then a monotonic increase in the number of false negatives can also be expected. If the sensing radius of the BLE signal in our simulation is set to 2 m (instead of the 10 m that was used to obtain Fig. 1), then there will be no possibility of occurrence for false positives. Then, a monotonic rise in false negatives can be observed as expected. Fig. 2 shows this trend when there are no false positives (i.e., sensing radius=2 m).

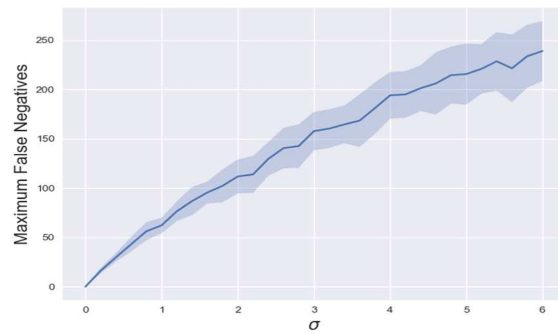

Fig. 2: Number of false negatives versus σ

To obtain the results in Figures 1 and 2, the instantaneous values of the estimated proximities have been used in the calculation of EEC and TEC. The instantaneous samples of the estimated proximities are most likely correlated in time and does not form an i.i.d. (i.e., independent and identically distributed) process. This is because the error samples are generated by the variation of the BLE signal strength when one or both individuals in close proximity move or change the positions. The correlation between the error samples in the estimated proximities is likely a function of the temporal correlation of the BLE wireless communication channel. This correlation can be exploited by using a proper windowing function to filter the sequence of estimated distances and lessen the impact of σ. For stationary individuals a simple rectangular window (averaging the sequence of estimated distances) can asymptotically mitigate the with increasing length of the window. We conjecture that the optimal length of this window for moving agents depends on the coherence time of the wireless channel. Estimation of this coherence time is quite challenging as it directly relates to the mobility pattern of the population under study as well as the movement (and possibly orientation) of their mobile phones.

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

In our preliminary study, we have observed that using a 3-point moving-average window significantly reduces the number of false exposure determinations for the mobility algorithm used in our platform. Figure 3 shows the results. The number of false negatives has increased to an average maximum of around 17; however, false positives occurrences has dropped significantly. Compared to the similar results in Fig. 1, using this simple filter has substantially reduced the total number of false exposure determinations. The average total number of false positives and false negatives versus time with and without filtering is also shown in Figure 4.

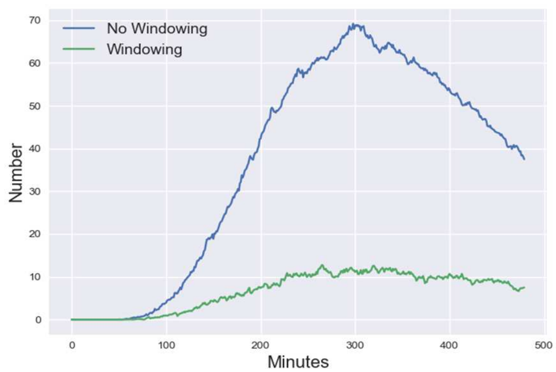

Fig. 4: Number of false exposure determinations during 8 hours of simulation ($\sigma = 2$)

IV. Conclusions and Future Work

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

The simulation platform presented here can be easily extended by incorporating additional mobility patterns for the agents. This will allow us to investigate the effect of each pattern on the resulting false exposure determinations. As briefly mentioned in the previous section, a more comprehensive study of the windowing function and its relationship with the agents' mobility pattern as well as the frequency of BLE signal measurement might also be beneficial to minimize the impact of σ on false determinations. Higher measurement frequency can potentially lead to higher accuracy in the estimated distance; however, it will drain the battery of the mobile phone. This would necessitate more frequent recharge when a contact tracing app is used. The authors plan to study the impact of the length of the time interval between consecutive BLE signal measurements using this simulation.

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