Poster Abstract: BluBLE, Space-time social distancing to monitor the spread of COVID-19

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Abstract: Social distancing has been the key factor which has helped control the COVID-19 pandemic spread. We present BluBLE, which utilizes Bluetooth Low Energy (BLE) based mobile sensing to help monitor these social distancing protocols. Specifically, we formulate the problem in two parts – spatial and temporal social distancing. The spatial distancing formulation aims to enforce the 6 feet distance recommended by various public health organization around the world. The temporal distancing formulation aims to inform and prevent users from entering high-occupancy regions (hotspots) in buildings. BluBLE achieved more than 80 % classification accuracy in both the tasks, that is, predicting if a user is within '6' feet of another user as well as characterizing the user's location within a particular hotspot.

CCS Concepts: • **Human-centered computing** → *Ubiquitous and mobile computing*; • **Information systems** → *Spatial-temporal systems*; • **Networks** → **Location based services**.

ACM Reference Format:
Aditya Arun, Agrim Gupta, Shivani Bhatka, Saikiran Komatineni, Dinesh Bharadia. 2020. Poster Abstract: BluBLE, Space-time social distancing to monitor the spread of COVID-19. In *The 18th ACM Conference on Embedded Networked Sensor Systems (SenSys '20), November 16–19, 2020, Virtual Event, Japan.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3384419.3430601

1 Introduction

The worldwide outbreak of COVID-19 in early 2020 has raised increased awareness on effectiveness of social distancing for controlling the spread of the COVID pandemic [2]. As trivial as the guidelines may seem – maintaining the 6 feet distance and avoiding crowded spaces – in practice, it is difficult to guarantee an effective social distancing paradigm. Hence, governments around the world have utilized mobile technologies to help enforce these social distancing norms.

One of the most popular usage of such technologies has been the digital contact-tracing mobile applications. The current deployments, which either utilize GPS based location sensing, or BLE-connectivity based proximity sensing often register contacts between people even if they are as far as 20 ft from the other person. This fails to meet the requirement for fine-grained contact-tracing to establish 'true' contacts between two individuals who are closer than 6 feet. This requirement arises from the fact that the disease transmits via airborne water droplets and aerosol particles, and we term this spatial social distancing.

Due to the evolving nature of these social distancing norms, this spatial problem also gains a temporal flavor. In the latter stages of the pandemic, policymakers are often forced to relax the social distancing norms, in order to re-open the economy and get back to normalcy. Here, it becomes critical not only to passively track the contacts, but also to collate information over time to get feedback on the implemented policies and take pre-emptive actions to avoid a second wave at the same time not hindering the re-opening process. An important application of these mobile technologies for aiding temporal social-distancing norms lies in identifications of new crowded hotspots being formed, in order to gauge the effectiveness of evolving social distancing policies. Furthermore, understanding the temporal distance between users in the same space opens up new doors to better understand COVID-19's transmission over fomite surfaces. Hence, peering through this dimension of time can help detect crowded hotspots, in turn guiding policy decisions on lock-downs and answering existing questions on COVID transmission.

BluBLE not only demonstrates increased accuracy in fine-grained spatial contact tracing, but is one of the first to target the temporal aspect by utilizing a novel hotspot detection mechanism. Keeping in mind widespread deployment, a critical requirement with such solutions is that the system must work robustly across different environments and mobile phone models. BluBLE aims to build such a robust system by performing crowdsourced data collection, and having classification accuracies for both the spatial and temporal tasks exceeding well over 80%, a set requirement to enforce effective contact tracing solutions [3].

2 Design

Next, we present BluBLE's proposed solutions to meet these stringent spatial and temporal social distancing requirements. For the first requirement, BluBLE attempts to classify if two people are within a distance of 6 feet from each other, as well as tracking the time of this contact. In the second requirement, we are looking to first determine, in an unsupervised manner, the number of crowded spaces (hotspots) in the environment given an initial training period. Next, we classify the subsequent samples (testing period) within these hotspots, as well as refine the density of old detected hotspots and track the new evolving hotspots. Hence, we are interested in both correctly predicting the number of hotspots in the tests we perform, and in classifying new readings to belong to a certain hotspot. For both of these tasks, the first step BluBLE takes is to build a crowd-sourced data collection platform to make the system generalizable across various environments.

2.1 Crowd-sourcing Data

Tackling the overarching requirement for widespread deployment, it is imperative for our algorithm to work across varying environments and different phone models. To accomplish this, we took to crowd-sourcing our data from different users across the campus. First we design a simple experiment which requires two BLE enabled devices, a 'mobile' device and a 'fixed' device. For the experiment, the users move, with their mobile devices, within and outside a 6-ft radius from the 'fixed' device. The 'fixed' device

SenSys '20, November 16–19, 2020, Virtual Event, Japan

ACM ISBN 978-1-4503-7590-0/20/11.
https://doi.org/10.1145/3384419.3430601

transmits BLE beacons, and the mobile device records the received signal strength parameter (RSSI) of these beacons as the user moves around. This allows us to investigate the correlation of RSSI and proximity between the mobile and fixed device.

To enable this experiment, we develop the RSSI data collection mobile applications for both iOS and android. Further, to enable a diverse set of devices to act as a fixed beacon, we give the users beaconing applications for Windows/Linux as well. We build a database with information about the phone's hardware, phone's IMU readings, BLE RSSI values and a corresponding label indicating the proximity (within or outside 6 feet) for each RSSI reading. Further information can be found on our website [1].

2.2 Fine-grained Spatial Social Distancing

Next, we tackle the requirement of identifying 'true' contacts based on proximity and duration of contact. We take a series of 5 consecutive RSSI measurements to form a feature vector. The beacon transmission rate is set to 5 Hz, and thus the feature vector takes RSSI readings collected over 1 second, and we get the proximity label from the mobile application which indicates if the user was within/outside the 6-ft radius for this 1 second of data collection. Now, we train an SVM classifier to classify the proximity labels of these feature vectors. We then test this classifier across all the environments' data in the entire dataset, achieving an accuracy of at least 74% in half the tests we performed. Next, assuming we have contextual information (i.e. is the space within a grocery shop, office space or outdoors), we train and test the classifier for this customized case and achieve an increased median accuracy of 96% (Fig 1).

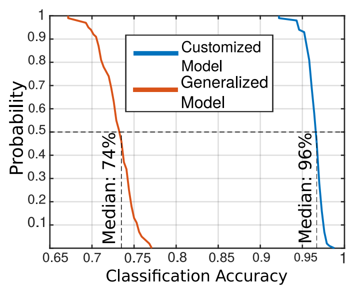


Figure 1. Proximity classification accuracy increases with contextual information about the environment

2.3 Temporal Social distancing and Hotspots

Finally, turning our attention to temporal social distancing, we are interested in identifying hotspots in an unsupervised manner, and classifying RSSI readings belonging to a particular hotspot. Here, we take a two step approach. During an initial 'training' phase, conducted for 30 mins, we allow users to freely use the environment, and congregate in groups. These users are carrying a smartphone with the BluBLE app and are collecting RSSI readings from bluetooth Tiles [4] placed in the environment (Fig 2 (a)). We take note of the number of groups formed and classify these as hotspots. Next, during the second 'testing' step, we ask a new user to walk in this environment, and again collect the same RSSI data. In these two steps, we aim to first detect the number of hotspots in the environment (Fig 2 (b)) and next classify sections of the user's path which belong to a certain hotspot (Fig 2 (c)). Furthermore, note that keeping the intent of large-scale deployment in mind, our proposed solution does not require large scale fingerprinting of spaces, but just passive observation of the space during a training phase. The duration of this training phase may increase given the size of the space, but there is no human-in-the-loop.

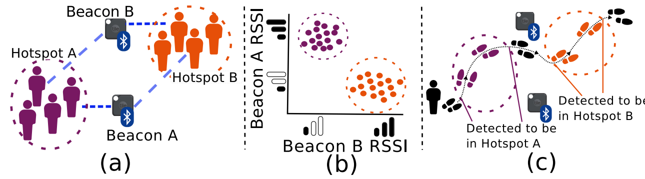
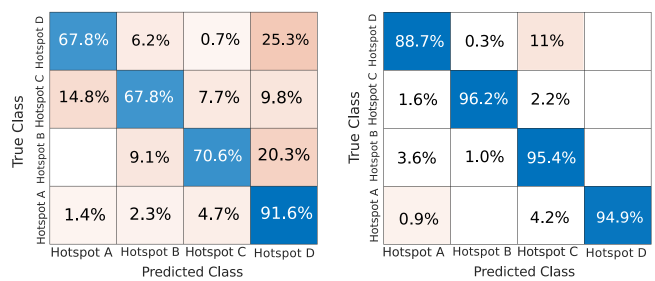


Figure 2. Classifying hotspots in RSSI domain from deployed beacons. In the figure we show how the hotspot detection algorithm works in a toy setting with 2 beacons

Specifically, we collect data for 2 deployment scenarios, with $T = 4$ and $T = 6$ number of tiles in the environment. Next, we artificially form 4 hotspots in the environment, by asking users to congregate at 4 known places. Here, one feature vector is a T dimensional entity consisting of RSSI readings from all the tiles in the space. Next, we employ k-means clustering over these feature vectors to identify the number of clusters in the environment, and then classify the 'test' T dimensional RSSI vectors into one of these 4 identified clusters. The accuracy of predicting the correct cluster is given in confusion matrix in Fig 3. Specifically, Fig 3 (a) achieves an agreeable classification accuracy with a deployment density of 1 tile per 144 sq ft, but these accuracies can be easily bumped up to meet our requirements by increasing the deployment density (i.e. 96 sq ft/tile).



(a) T=4 beacons (144 sq ft/beacon) (b) T=6 beacons (96 sq ft/beacon)

Figure 3. Confusion matrices for Hotspot Classification

3 Conclusion

In this poster we presented BluBLE, a robust and fine-grained contact tracing system, which can provide both spatial and temporal social distancing. Through this two pronged approach, we are firstly able to accurately detect 'true' contacts between two users. Secondly, we are able to automatically detect crowded spaces in indoor environments and classify the users within these detected hotspots. Looking at this from a policy-making lens, enabling spatial social distancing, it is easily possible to enforce 6-feet distancing among people. Furthermore, detecting hotspots will allow for targeted closures of building facilities to discourage congregations during this uncertain times of office re-openings. Taking in the larger picture, an automated system to detect hotspots allows for crowd management within buildings, enables better fire safety and more efficient use of building resources.

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