Bluetooth Proximity Estimation by Signal Strength

Nathaniel de Lautour, Logan Small, John Harris, Matt Hopkins
Defence Technology Agency
NEW ZEALAND DEFENCE FORCE
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1. EXECUTIVE SUMMARY

Bluetooth-based proximity apps are currently of intense interest as an enhancement to manual contact tracing for controlling COVID-19. This report discusses the accuracy of distance estimation that can be achieved using Bluetooth proximity apps, and highlights potential problems based on the known characteristics of Bluetooth radio signals. It does not discuss the details of currently available implementations or data handling and privacy issues, which are still rapidly evolving at the time of writing.

Proximity apps work by transmitting and receiving Bluetooth Low Energy signals and estimating distance between smartphones using the received signal strength. However, these distance estimates may be subject to significant errors resulting in both false contacts, and actual contacts which are missed. In addition, Bluetooth signals can pass through walls and cause false contacts even if the distance estimate is accurate.

Resolving false contacts generated by Bluetooth proximity apps could result in a heavy workload for investigators. We recommend delaying the integration of Bluetooth functionality into contact tracing apps until real-world performance is better understood.

2. INTRODUCTION

Effective contact tracing is essential for infectious disease control and is currently the subject of intense New Zealand effort to combat coronavirus disease 2019 (COVID-19). Traditional contact tracing requires an investigator to uncover all recent social interactions of an infected individual, a time-consuming and labour-intensive process. Supplementing manual contact tracing with digital methods has been recently discussed and the potential benefits studied [1].

The use of the Bluetooth Low Energy advertising channels has recently been proposed as a method for determining distance between smartphones for COVID-19 contact tracing purposes. Signal strength decreases with distance and so, in theory, distance could be estimated from a measurement of signal strength by a smartphone app. The Low Energy extension of Bluetooth would permit the app to be run continuously without excessive battery drain.

Some success has been achieved with Bluetooth Low Energy for indoor positioning, in which multiple static Bluetooth beacons can be used to locate a mobile Bluetooth receiver. However, estimating distance between two mobile devices using signal strength alone is a more challenging problem. This document discusses the key elements of Bluetooth signal detection and implications for the use of signal strength as a proximity or distance estimator. An overview of current development efforts around the world and the different standards they adhere to have been discussed in [2].

This report presents a quick review of the technical feasibility of proximity estimation between smartphones using Bluetooth. The key factors affecting Bluetooth signals are outlined, and the technical challenges these present for proximity or distance estimation are described. Finally, the limitations of Bluetooth for COVID-19 contact tracing, including the risk of false contacts, are discussed.

3. BLUETOOTH LOW ENERGY

Bluetooth Low Energy (BLE) devices use 40 channels, each with a 1 MHz bandwidth, evenly spaced between 2400 MHz and 2483 MHz in the band allocated for Industrial, Scientific and Medical (ISM) applications. BLE is intended for applications where low power consumption is a necessity and minimal amounts of data are exchanged. BLE has four operation modes: master, slave, advertising and scanning [3]. Three of the BLE channels (37, 38 and 39) are used for the advertising mode, and the remaining 37 channels are designated as data channels, as illustrated below in Figure 1.

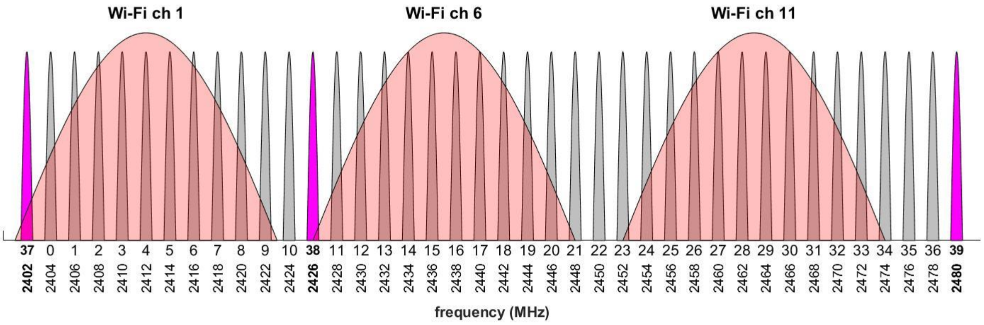

Figure 1. The 40 Bluetooth channels (including the three BLE advertising channels 37, 38 and 39) and Wi-Fi channels 1, 6 and 11 in the 2.4 GHz ISM band.

The BLE advertising mode enables short, unsolicited messages to be transmitted at variable rates. To reduce interference the advertising channels are positioned away from the most commonly used 2.4 GHz band Wi-Fi channels (1, 6 and 11). BLE also uses frequency hopping over the 37 data and three advertising channels to further mitigate interference and fading losses.

Because signal strength decreases with distance from the transmitter, in theory a smartphone could measure signal strength and work backwards to estimate the distance of the source. This is dependent on an established and consistent relationship between signal loss and distance, known as a path loss model.

4. RECEIVED SIGNAL STRENGTH INDICATION

The signal strength is typically expressed in units of dBm, which is the logarithm of the power in milliwatts with a reference level of 1 milliwatt (mW). In Wi-Fi and Bluetooth chipsets the signal power is converted to an integer value known as the Received Signal Strength Indication (RSSI) and is used internally. Depending on the manufacturer, the driver software for the chipset may convert the RSSI value to a power level in dBm which can be used in mobile device apps. Although the RSSI may be converted to actual received power in dBm by the driver software it is still generally called the RSSI. On some platforms, the conversion is not performed and only the integer RSSI value is made available [4].

5. TRANSMISSION POWER

The BLE standard was first introduced as part of Bluetooth 4.0. In that version of the standard BLE transmit powers were permitted from -20 to 10 dBm. In Bluetooth 5.0, the maximum permissible power has been increased to 20 dBm. In a recent test of a dozen devices in Singapore (including an iPhone 6), the average received signal strength of BLE advertising signals varied from -70 to -50 dBm [5]. Clearly, one can expect transmit power to differ significantly across the population of smartphones, and this must be accounted for in distance estimation algorithms.

6. PATH LOSS AND ATTENUATION

Path loss is the reduction in signal strength with distance from a transmitter. In free space the path loss in decibels is $20\log_{10} d$ where d is the distance, which is simply the familiar inverse square law in logarithmic units. If the path loss were always governed by this simple law then distance estimation would be straightforward, if the transmitter power is known and the signal strength can be measured.

However, there are many complicating factors in real-world environments. The difficulty in obtaining consistent path loss models is a well-known problem for wireless sensor networks [6].

A significant contributor to fluctuations in path loss is a phenomenon called multipath interference, in which reflections of the transmitted signal from objects combine and interfere with the wave that travels directly to the receiver. This can cause temporary but severe fluctuations of the received signal strength, an effect known as multipath fading.

Radio waves can be significantly attenuated when passing through absorbing materials depending on size, thickness, composition and the radio frequency used. Bluetooth signals can pass through walls, floors and windows that would prevent direct infection, but may trigger a distance and/or contact duration threshold on a contact tracing app.

Attenuation for common building materials near Bluetooth frequencies (2.3 GHz) are given in [7]. Some of the losses reported were (approximately): plexiglass 0 dB; glass 0.5 dB; brick 4.5 dB; drywall (12.8 mm) 0.5 dB; cinder block 7 dB; stucco (which was 1 inch concrete with a steel mesh backing) 15 dB.

Fluctuations in Bluetooth signal strength of 20 to 30 dBm were reported by Jung et al. with a hand-held mobile device [8]. Similar results were reported by Faragher et al. in [9], who noted 30 dBm fading losses with just 10 cm of antenna movement. The fading effect for Bluetooth is significantly worse than Wi-Fi because the Bluetooth channel bandwidth is narrower [9]. Recent signal strength measurements between two Raspberry Pi devices performed by DTA also noted this phenomenon [10].

Mobile devices are often placed in pockets when not in use. The radio signal path from one device to another may have to pass through the body of the user(s) and will suffer attenuation. The 2014 experiments by Faragher et al. encountered 10 to 15 dB body attenuation losses [9]. These values are comparable to losses reported in [11] for a user with a mobile phone in a pocket transmitting to a Bluetooth headset. In this latter case the loss also ranged from 10 to 15 dB, depending on device orientation. Some of these losses may be due to adverse antenna orientation, rather than body attenuation, as discussed in the next section.

7. ANTENNA ORIENTATION EFFECTS

Antennas for portable devices need to be compact and fit into the slim form factor of mobile phones and tablets. Two antenna types are in common use in mobile devices – ceramic dielectric resonator (“chip”) antennas, and printed circuit antennas. Ideally, the Bluetooth antenna on a mobile device would project radio signals equally in all directions. In practice, the strength of emitted radio waves depends on the direction, and this dependency is called the antenna radiation pattern.

Due to time and cost full 3D antenna radiation patterns are not routinely measured, and there is little information available regarding antenna directivity for mobile devices [12]. Reference [11] contains 2D radiation patterns of a Bluetooth Printed Inverted F-Antenna (PIFA) in a Sony Ericsson K750i mobile phone. The antenna patterns shown have two nulls[1] one about -20 dB and the other -30 dB from the maximum response. The remainder of the pattern is omni-directional within about ±5 dB. These are broadly comparable to the Bluetooth PIFA radiation patterns given in [12].

The worst-case scenario for antenna losses occurs when the transmitter and receiver are oriented so that the line-of-sight path is through nulls in both transmit and receive radiation patterns. For example, with a 20 dB null in each antenna the total directivity loss could be as high as 40 dB. In practice, mobile devices are usually in constant movement and these extremes would be rarely encountered. But a 20 dB loss, caused by a user rotating a device, could be encountered quite frequently.

[1] A *null* is a local minimum in the antenna radiation pattern.

8. BLUETOOTH LOW ENERGY INDOOR POSITIONING SYSTEMS

BLE based indoor positioning is a technology used to locate people in shops, malls and workplaces for targeted advertising and data collection. Attempts to use Bluetooth for indoor positioning date back to the early 2000s, using both proximity and lateration approaches [13]. However, scanning times with classic Bluetooth were too large and not suitable for accurate low latency positioning.

With the development of BLE in 2012, the iBeacon and EddyStone specifications and the availability of cheap beacons, BLE has increased in popularity for indoor positioning. Indoor positioning systems utilize several static BLE beacons and estimate position by synthesizing RSSI measurements of each beacon. An indoor positioning system can use static and well calibrated beacons, carefully placed to improve coverage and accuracy. An extensive 2019 review of all technologies used for indoor positioning systems, including BLE, is given in [14].

Performance and operation of indoor positioning systems based on BLE are not comparable to distance or proximity estimation between two mobile devices for contact tracing. The indoor positioning problem has the advantage of multiple beacons and allows for experimentation with beacon placement. Proximity or distance estimation between mobile devices is a more difficult problem that requires alternative approaches.

9. DISTANCE AND PROXIMITY ESTIMATION WITH BLUETOOTH

Three broadly different approaches have been used to estimate distance in wireless sensor networks: time of arrival, time difference of arrival, and signal strength [15, 6, 8]. The time of arrival (TOA) technique has been successfully used for the GPS where atomic clocks in the satellite constellation provide very accurate timing. But it is not feasible to use TOA methods between wireless sensors a few metres apart because of the extremely precise timing required.

Time difference of arrival (TDOA), on the other hand, exploits the difference in propagation speeds for two different signaling mechanisms. TDOA methods using ultrasound and radio signals have been proposed for mobile devices, in which the radio signal is assumed to travel at infinite speed and provides a time origin to measure ultrasound propagation time [6]. For contact tracing, ultrasound distance measurement would be an advantage because high frequency sound is blocked by thin partitions. However, it could also be a disadvantage as the signal may be blocked by a phone placed in a pocket. It also imposes higher computational costs for processing of the acoustic signal and additional power to transmit the signal.

The received signal strength indication (RSSI) can also be used for distance estimation using the principle that signal strength decreases with distance from a transmitter. In an environment free from obstacles the decay with distance is the inverse square law. But in real environments there are reflections, and the signal can be absorbed or blocked, so that the signal strength does not usually follow this simple model. For practical real-world use, a path loss model needs to be calibrated from experimental measurements.

A 2013 paper by Jung et al. attempted distance estimation between Bluetooth devices using polynomial fits to RSSI vs. distance data [8]. A similar approach was used prior to this for an indoor positioning system, with multiple transmitters and a single receiver [13]. The authors in [8] used a polynomial curve fitting approach to RSSI data collected in three different indoor environments. Fluctuations in the raw RSSI values were in the range 20 to 30 dBm, and time averaging was used to reduce this to around 10 dBm.

When this method was applied to data collected in an electromagnetic test chamber[2] it was possible to estimate distance to an accuracy of about one metre out to six metres range. Beyond six metres, distance estimation became unreliable due to residual fluctuations. The authors then tested this

[2] A room in which the walls are coated with absorbing material to prevent reflections of radio waves from a device under test.

method with data collected in a hall and a meeting room. In these tests the residual (after filtering) RSSI fluctuations are much larger, and distance estimates based on curve fitting will be inaccurate.

To apply the method of [8] in practice would require measurements in a variety of conditions, to yield an average or representative path loss model for use by a smartphone app. It is possible this approach could give useful distance or proximity estimates. But to be confident would require significant additional data collection, algorithm refinement and testing above that reported in [8].

In an alternative approach, also using RSSI, a 2015 paper by Kim et al. presents a method to detect a device moving inside a proximity zone [16]. The proximity zone criterion was based on counting the number of RSSI values exceeding a minimum signal strength in a moving time window, and was satisfied when that count exceeded a threshold value. Appropriate thresholds and time windows depend on the size of the desired proximity zone and must be fixed by experiment.

The rate at which RSSI was sampled was not stated explicitly but appears to be around five per second. Additionally, the authors attempted to detect when a user stops inside the proximity zone by sampling the device's accelerometer, and then ignoring detections when the device was moving. In experiments with a fixed beacon and a hand-held smartphone the proximity detection method of [16] achieved an error rate of 12% or less, for a designated proximity zone distance of 0.5 m. Distortion of the proximity zone was observed, presumably due to antenna radiation pattern loss and possibly multipath effects.

In a 2017 paper by Huang et al. [17] the authors estimate distance using a similar approach to Jung et al. in [8], but with a running median filter on RSSI to smooth the fluctuations. The results indicate the median filter was more successful in suppressing noise than the averaging methods in [8]. However, practical implementation again depends on designing a path loss model, which would require additional data collection and testing.

More rapid sampling of RSSI may improve the speed and accuracy of the methods in [8], [16] and [17]. But higher sampling rates might require hardware changes – which is impractical – and would deplete the battery faster.

Note also that the experimenters in [8] used statically mounted receivers and transmitters, while those in [16] used a static beacon and a hand-held receiver. Neither group has reported tests on the effect of having both devices either hand-held or in a pocket.

10. DISCUSSION

Proximity measurements between smartphones using Bluetooth will depend on an established relationship between RSSI and distance (a *path loss model*, as discussed in Section 6). The strength of the Bluetooth signal depends on several factors: the transmission power; signal fading due to multipath interference; attenuation from obstacles (including the human body); the effect of changing antenna orientation.

The magnitude of each of these factors will be environmentally dependent. In practice, a smartphone app will use a single path loss model obtained from experiments intended to model real-world propagation conditions. But random variations due to multipath, changes in antenna orientation and the presence/absence of body attenuation, can result in 10s of decibels in signal strength change. For reference, a 20 dBm change in RSSI is equivalent to a factor of ten change in distance in free space.

A number of papers were reviewed in Section 9 in which the authors attempted to mitigate these effects by time averaging, but the experimentation was performed in a limited range of environments and conditions. More data collection, algorithm refinement and testing in real world conditions is needed to gain confidence in these methodologies.

A false contact, i.e. a Bluetooth contact event that was not an infection risk, could be caused by fleeting but high RSSI levels. This type of false contact could be mitigated in a smartphone app by requiring a minimum Bluetooth contact duration to be used in addition to a distance threshold.

False contacts can also be generated by detection of Bluetooth signals through walls, floors and other barriers, where there is no direct infection risk. These events would need to be resolved by a contact tracing investigator.

11. Conclusions

Based on the properties of Bluetooth radio signals, and current approaches to using these signals for proximity estimation, we conclude that:

- Bluetooth signals are affected by fading, body attenuation, and variations in antenna loss. These factors can lead to significant errors in distance estimates and are difficult to mitigate;
- A contact duration threshold could be used to reduce false contacts caused by strong but fleeting Bluetooth signals;
- Persistent Bluetooth signals may still pass through floors, walls and other physical barriers resulting in false contacts.

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