Co-location Epidemic Tracking on London Public Transports Using Low Power Mobile Magnetometer

Khuong An Nguyen
Department of Computer Science
Royal Holloway, University of London
Surrey, United Kingdom
Email: Khuong.Nguyen.2007@live.rhul.ac.uk

Chris Watkins
Department of Computer Science
Royal Holloway, University of London
Surrey, United Kingdom
Email: C.J.Watkins@rhul.ac.uk

Zhiyuan Luo
Department of Computer Science
Royal Holloway, University of London
Surrey, United Kingdom
Email: Zhiyuan.Luo@rhul.ac.uk

***Abstract*—The public transports provide an ideal means to enable contagious diseases transmission. This paper introduces a novel idea to detect co-location of people in such environment using just the ubiquitous geomagnetic field sensor on the smartphone. Essentially, given that all passengers must share the same journey between at least two consecutive stations, we have a long window to match the user trajectory. Our idea was assessed by a painstaking survey of over 150 kilometres of travelling distance, covering different parts of London, using the overground trains, the underground tubes and the buses.**

I. Introduction

In 2015, it was reported that over 3 millions people relied on public transports in London every day, with an average of 45 minutes on board per person[1]. Such condition is ideal for infectious diseases to spread. For instance, an ill person's openly sneeze or cough may easily spread to other fellow passengers on a poorly ventilated underground tube in a long journey. Thus, co-location detection of people in such highly infectious environment is critical to control or predict the disease spreading rate in an event of epidemic.

Over the last decade, the emergence of the mobile devices presents a unique opportunity to tackle this challenge, since most people carry a smartphone with them when they are out and about. More importantly, modern smartphone is equipped with multiple sensors that are capable of passively scanning the surroundings. However, little work was done within the healthcare research community to make use of these sensors' reading. In this paper, we propose the use of the geomagnetic field sensor (magnetometer) to detect co-location of people on the public transports. We assume that, when two mobile devices observe similar time-stamped sensors' readings, they should be nearby, which in turn, indicates that their respective owners should also be close by. Critically, since every passenger must share the same journey between at least two consecutive stations, which may last up to 10 minutes on the trains or buses, we have a window of opportunity to assess co-location of people.

The foremost advantage of our approach is that, at the time of writing, Google consider magnetometer to be a low power basic sensor, and thus, allowing it to be always-on and can be inquired without any permission, even in flight-safe mode. This is important for any passive epidemic tracking app to run seamlessly without the hassle of asking for the user permission (e.g. Since Android 6.0, Google demand any app that uses WiFi or Bluetooth to ask for real-time permission to access the user location).

Overall, the paper identifies the following contributions:

- We propose the use of magnetism to detect co-location of people. No wireless signals (e.g. WiFi, Bluetooth, GPS, and Cellular) are needed.
- We detail our algorithm to robustly detect same-carriage co-localisation.
- We assess our system in large scale real-world settings which cover 150 kilometres of travelling distance in different parts of London on all types of public transports (i.e. the overground trains, underground tubes, and buses).

The remaining of the paper is organised into five sections. Section II tells the story behind our ideas of using magnetism. So that, Section III can build on to explain our concept of magnetic based co-location, emphasising on the challenges facing such approach. Then, Section IV details the experiments including the test environments and the empirical results. Section V overviews other related work. Lastly, Section VI summaries our work and outlines further research.

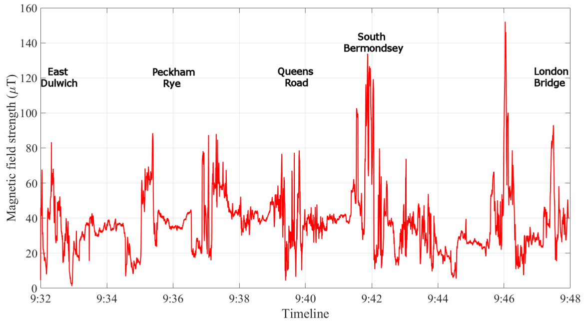
II. Magnetism based co-location of people

This section justifies the selection of magnetism for this paper and compares it to other wireless based competitors.

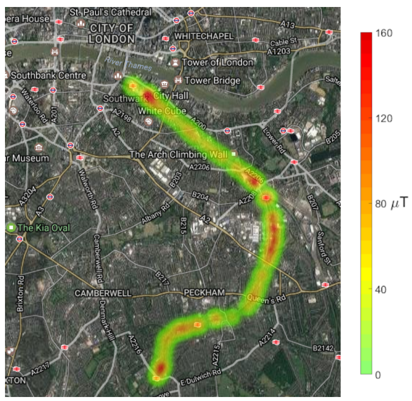
A. An inspiration for using magnetism for co-localisation

It is well-known that animals rely on the Earth's magnetic field to perform route-finding in nature (e.g. the birds know where to head North in migratory season). Regrettably, such technique cannot be applied indoors or undergrounds, because the natural magnetic field generated by the Earth's core is heavily distorted by the metal bars, steel rebars, ferrous tubes and reinforced concrete which are commonly found within the building structure. Additionally, an electric current that moves in metal wires (e.g. power lines) will alter the nearby magnetic field. However, this challenge provides a 'unique' opportunity for the purpose of localisation. That is, the magnetic field is

[1]https://www.gov.uk/government/statistics/transport-statistics-great-britain-2015 - last accessed in Feb/2017



(a) High level of magnetism distortion during a 16 minute train journey



(b) The heatmap visualisation of the trip

Fig. 1. An inspiration for using magnetism for co-location detection on public transports. The magnetism observed on-board of an overground train from South-East to Central London, passing through 5 stations is heavily distorted.

not uniformly perturbed, so that, different locations experience different magnetism anomalies (see Figure 1).

Nevertheless, the ultimate research question is: **"To what extent can magnetism be used to differentiate two separate positions?"** For the purpose of epidemic tracking, we are looking at city-level operation, and it is unavoidable that several locations may exhibit a similar magnetic signature. There are four reasons that inspire us to venture towards this approach.

1) We are only interested in co-localisation, that is, the exact moment two persons are close by. As such, a time stamp constraint will get rid of most similar samples collected at other periods.
2) We focus our attention on the public transports, which guarantee that all passengers must follow the same trajectory between at least two consecutive stations. This window supplies a long sequence of samples allowing us to further differentiate non-co-located users.
3) Modern public transports are electric-based (e.g. those used in London) which greatly alters the on-board magnetic field. Besides, other trains that run on adjacent tracks may temporarily distort the magnetism on the neighbourhood trains.
4) The ferrous structure from nearby buildings may possess a unique magnetic signature that all passengers on the same train must observe when passing by, albeit with different time delays (i.e. the passenger at the front of the train will 'see' the upcoming building a few seconds earlier than the one at the back).

B. The pros and cons of using magnetism

For the purpose of co-location that leverages the smartphone's sensors, the magnetic field strength is not the only viable option. Other popular wireless signals such as Bluetooth, WiFi, Cellular, GPS have their own pros and cons (see Table I).

Coverage-wise, the magnetic field is available anywhere on Earth, whereas, GPS, WiFi, Bluetooth and Cellular wireless signals depend on the distance to nearby stations or satellites. In terms of power level, five hours of magnetometer's continuous inquiry plus writing the results to a file consumes as little as 7% of battery, according to the in-built Android power measure, compared to over 45% of that using GPS, and 30% using WiFi. As a matter of fact, Android even allows the magnetometer to function normally in both 'Flight safe' mode and 'Power saving' mode, where most other sensors are suppressed or turned off completely. Additionally, the magnetometer achieves a fine-grained sampling rate at about 49.65 Hz on both of our test phones (about 50 samples per second), compared to just 3 samples per second with Bluetooth or about 1.5 samples with WiFi. It is worth noting that since Android offers 3 levels of magnetometer sampling - 4.96 Hz, 14.89 Hz and 49.65 Hz, we opted for the fastest one. This is essential for the underground tube test scenario, where the average speed of the tube is 60 kilometres per hour. Lastly, the ease of access is probably the most overlooked strength of the magnetometer, for which no permission whatsoever is required from either the user or the app to inquire the sensor's readings, at the time of writing.

However, despite these apparent benefits, the magnetic field strength is not spatially unique, because it contributes just 3 measures at each position, corresponding to the strength along each of the 3 axes (see Figure 2). In contrast, WiFi or Cellular based solutions have a much richer positioning representation, since they obtain references from several nearby stations. More problematically, the 3D orientation of the phone varies the above measures. As such, the 3 measures must be reduced into one total scalar magnitude (i.e. $\sqrt{(X^2+Y^2+Z^2)}$), which practically means we only have one magnetic field based measure for every position.

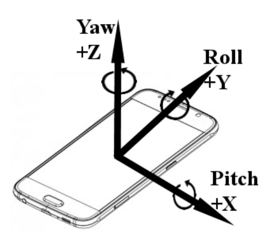


Fig. 2. The three axes measured by the magnetometer.

TABLE I
COMPARISON OF SMARTPHONE BASED SENSORS FOR CO-LOCATION PURPOSE.

	Magnetometer	WiFi	Bluetooth	Cellular	GPS
Coverage	Ubiquitous	Mostly indoors & City centrals	Indoors	Urban areas	Outdoors
Ease of access	No permission	Need user permission	Need user permission	Need user permission	Need user permission
Power consumption	Low	High	Low	Average	Very high
Sampling rate	49.65 Hz	1.5 Hz	1 Hz	0.1 Hz	1 Hz
Spatial uniqueness	Changing	Changing	Changing	Low	High
Temporal variation	Low	High	High	High	Low

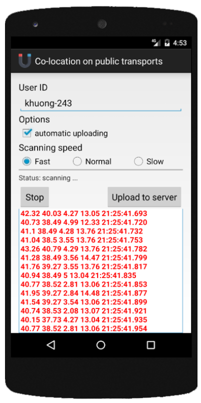


Fig. 3. The Android app used to collect the magnetic field strength.

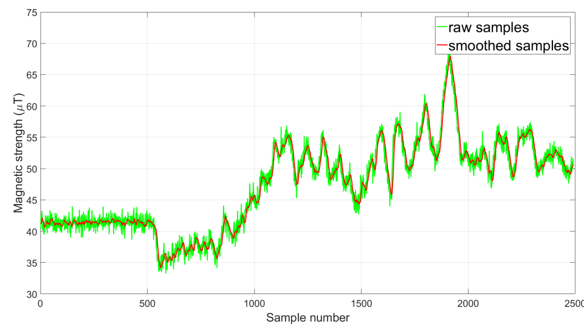


Fig. 4. A part of the magnetic sequence with/without the moving average filter. The filter reduces the overall electric noises from the magnetometer.

III. ANALYSING THE SENSOR'S FOOTPRINTS FOR CO-LOCATION DETECTION

Now we are in a good position to explain our co-location detection idea. At the beginning, the user installs an Android app on his device (see Figure 3). The app's mission is to silently collect the magnetic field strength in the background. Each magnetic reading is accompanied by a time stamp and an activity recognition parameter, which will be discussed shortly. In an event of epidemic, the user submits his personal sensor data to a central server, which also manages other users' data. The process of co-location detection will be performed by comparing each pair of user data as follows.

Without loss of generality, let us assume the first user - Alice submits her data in the form of $(\vec{p_1}, \ldots, \vec{p_N})$, where $\vec{p_i} = (m_i, a_i, t_i)$ is the representing vector of position i^{th} on Alice's journey comprising of N positions. m_i is the scalar magnitude reported by the magnetometer and a_i is the recognised activity (to be discussed below) at time t_i $(1 \leq i \leq N)$. The second user - Bob's trajectory is in a similar format of $(\vec{p'_1}, \ldots, \vec{p'_M})$. Our objective is to verify whether Alice and Bob were co-located, and if so, when did that happen?

Step 1: Smoothing the data

We applied a linear moving average filter on the magnetometer outputs to smooth out the short-term electric noises from the sensor and to expose the true magnetic changes generated from the vehicle and the environment (see Figure 4). An empirical window size filter of 10 was applied, since we can acquire up to 50 samples per second. Without loss of generality, given a sequence of magnetic readings $(m_1, \ldots, m_N)(11 \leq i \leq N)$, with N is the length of the sequence, each magnetic sample is smoothed out as follows.

$$m_i = \frac{\sum_{j=1}^{10} m_{i-j}}{10} \tag{1}$$

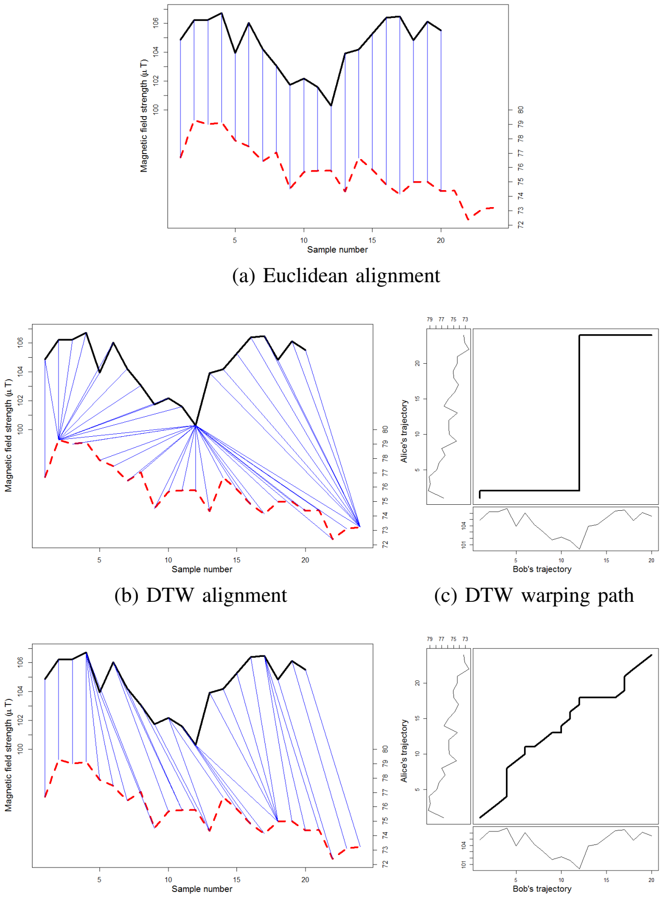
Step 2: Filtering the public transport related sequences

The user's sensor data reflects his continuous activities through out the whole recorded period. However, we are only interested in parts of the data where the public transports were used. Hence, we employ the Activity Recognition API provided by Android to extract those[2]. This process runs in real-time along side with the data collection. The crux of this algorithm is a Bayesian classifier that decides the likelihood of the current activity based on the current sensors' readings. Eight different activities are supported (i.e. Walking, Running, Still, On Foot, On Bicycle, In Vehicle, Tilting and Unknown). For our purpose, we are only interested in the 'In Vehicle' and 'On Foot' activity. A magnetic sequence will be extracted if it begins with an 'On Foot' event, following by an 'In Vehicle' event, which signals that the user is entering the train or bus, and ends with another 'On Foot' event, which signals that he is leaving the vehicle. At the end of this step, each user's data is split into multiple trajectories, for which, each of them represents a separate trip on a public transport.

Step 3: Finding the pair of matched trajectories

Each of Alice's trajectories will be compared to all of Bob's trajectories to determine if they were co-located. The reverse process is unnecessary since the relationship is both-sided. We

[2]https://developers.google.com/android/reference/com/google/android/gms/location/ActivityRecognitionApi - last accessed in Feb/2017.



(a) Euclidean alignment

(b) DTW alignment

(c) DTW warping path

(d) Derivative DTW alignment

(e) Derivative DTW warping path

Fig. 5. The justification for using Derivative DTW. Euclidean distance based matching fails to align trajectories of different lengths, while standard DTW over-warps the X-axis to explain the variability of the Y-axis.

employed Derivative Dynamic Time Warping (DDTW) [1] to match two magnetic trajectories for four reasons.

Firstly, it stretches the shorter trajectory to match the longer one, which is essential for our purpose because of different sensors' sampling rates. Secondly, it can match mis-aligned trajectories by finding the optimal warping path which is important due to various sensitivities from different sensor models, whereas other distance-based measures (e.g. Euclidean, Manhattan) simply align the i^{th} point on Alice's time series to the same i^{th} point on Bob's time series (see Figure 5a). Thirdly, DTW is a proven technique with successful time-tested applications in the speech recognition research community [2].

Lastly, our justification for using DDTW instead of the standard Dynamic Time Warping (DTW) is that DTW may suffer from incorrect alignments where a single position on Alice's trajectory is mapped onto a large set of positions on Bob's trajectory (see Figure 5b). This phenomenon commonly happens when standard DTW tries to explain the variability of the Y-axis by over-warping the X-axis (see Figure 5).

Without loss of generality, given Alice's magnetic sequence $A = (m_1, \ldots, m_N)$ and Bob's magnetic sequence $B = (m'_1, \ldots, m'_M)$, DDTW tries to build an N-by-M matrix, where the $[i^{th}, j^{th}]$ element is the distance between the two points m_i and m'_j. While standard DTW uses the Euclidean distance, DDTW uses the square of the difference of the derivatives of m_i and m'_j as follows. This distance was empirically proven to be more robust to outliers than other estimates using only two data points [1].

$$D(A) = \frac{m_i - m_{i-1} + ((m_{i+1} - m_{i-1})/2)}{2}, (1 \leq i \leq M) \tag{2}$$

Step 4: Validating the matching pairs of trajectory

Given one of Alice's trajectories, DDTW will always find a best matched trajectory from Bob's (i.e. the one with the smallest distance), although they may not be similar at all. This is a typical challenge for all distance-based and similarity-based approaches. For a highly sensitive task such as epidemic tracking, an administrator normally looks at the final matching trajectories presented by the algorithm from the last step, and manually decides whether they are indeed co-located or not. Nevertheless, we present three heuristics to automate this decision-making process.

1) The temporal difference of the two trajectories must be less than 5 seconds. For a typical 8-carriage train in London, it is unlikely that Alice and Bob are in the same carriage if their trajectories are distanced by more than a few seconds apart.
2) The compression rate must not exceed an empirical constant of 1.5. This number measures how stretched or compressed one trajectory is, in order to match the other trajectory. Realistically, we expect the journey of two co-located passengers to be roughly equal in terms of length. Given the length of Alice's magnetic trajectory is l_A (samples) and Bob's is l_B (samples), the compression rate is calculated as $\frac{max(l_A, l_B)}{min(l_A, l_B)}$.
3) The DDTW score of the two trajectories must not exceed an empirical constant of 5. This score is calculated by adding up the difference between every aligned samples on the time series, divided by the total length of the warped path.

A pair of trajectories must satisfy all three above criteria to be declared as valid matching, and thus, signalling a co-location detection between the two respective passengers. We will evaluate their performances in the experimental section.

A. Challenges to our approach

Firstly, for any technique that aims to differentiate the users' position, the spatial uniqueness of the sensor reading is essential. Although our approach takes into account a time series of the readings, if the user rides a very short trip, it is much harder to match his trajectory to other passengers'. We will assess this challenge in the experimental section.

Secondly, time-wise, all phones must be synchronised to correctly co-locate their owners. Since the app uses the local time on the phone to stamp each sensor output, some mismatch among different phones' clock may occur. A simple solution is to inquire an internet time service for ground-truth, whenever a connection can be made. This ground-truth will help revealing the offset to the phone's local time.

Thirdly, the heterogeneous devices remain a difficult task for any smartphone based approach. Phone makers may employ non-identical chip sensors, which have different sensitivities. However, our algorithm does not rely on the absolute strength value but the overall shape of the trajectories to match them.

IV. Empirical experiments

This section conducts the experiments to assess the feasibility and the accuracy of our approach. In doing so, it aims to address the following research questions.

In terms of feasibility:

- **How much spatial variation does the on-board magnetism possess?** High variation of magnetism amongst places is highly desirable to generate a distinguishable trajectory for people in different carriages.
- **How identical is the magnetic field strength in the same train carriage or bus?** We hypothesise that nearby passengers at carriage-level should observe a similar magnetic reading at any moment.

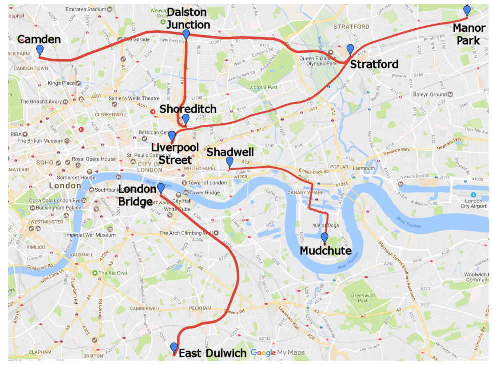
In terms of accuracy:

- **What is the precision and recall rate (i.e. true, false positives) of our co-location detection algorithm?** We will verify the successfulness of our detection algorithm on real-world data.

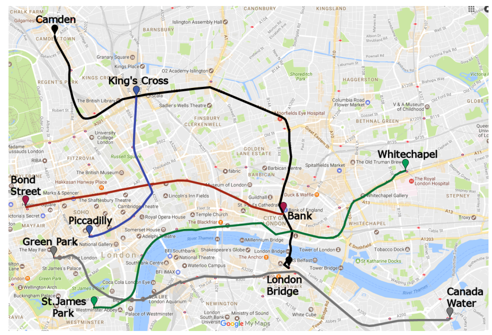
For the ease of assessment, the experiments were categorised into three scenarios - the overground train, the underground tube and the bus (see Table II). Different types of vehicles were also tested (i.e. London trains are operated by 22 different companies). Two Android phones were used in this research, namely the Google Nexus 5 (released in 2013, running Android Lollipop), and Lenovo Phab 2 Pro (released in 2016, running Android Marshmallow). Through out the following experiments, these devices were either held naturally in the surveyors' hand, or left in the pocket. Their local clocks were also synchronised by manually setting the time in advance.

TABLE II
Key highlights of our test environments.

	Overground train	Underground tube	Bus
Average speed	30 km/h	60 km/h	20 km/h
Carriage length	20.4 m	16.1 m	11.1 m
Carriage width	2.8 m	2.6 m	2.5 m
Co-located trajectories	26	34	38
Distance coverage	70 km	57 km	22 km
Max # coaches	8	7	2
Magnetic variation	Moderate	High	Low
Non-co-located trajectories	26	34	38
Powered by	Electricity	Electricity	Diesel-electric
Shortest trip	5 minutes	1 minute	1 minute
Total stops	31	39	42



(a) Overground train test routes. They cover over 70 km, passing through 2 of the busiest stations in London (London Bridge & Liverpool Street).



(b) Underground tube test routes. The routes shown here are exactly the same as the real-life ones. Since the tubes travel underground, some paths appear to go under-water and through buildings.

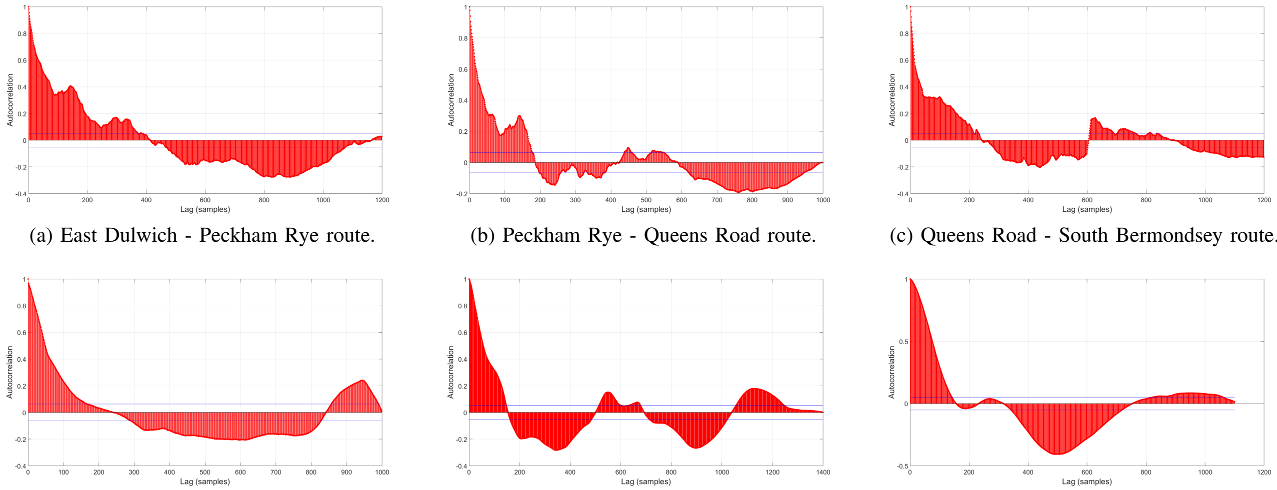
Fig. 6. The overground and underground test environments visualised on Google Maps.

A. *Overground train and underground tube test environments*

As the overground trains and underground tubes share similar aspects (i.e. both have multiple carriages, are electric-based), we combined both test environments for more concise analysis.

Our overground test scenario composes of 5 separate routes, which traverses 31 different stations, and covers over 70 kilometres of travelling distance in the South-East and East-Central of London (East Dulwich - London Bridge - Camden - Liverpool Street - Stratford - Manor Park) (see Figure 6a). Our underground tube test scenario examines 5 main lines of the London underground network, namely the Northern, Central, Jubilee, Piccadilly and District lines, covering over 57 kilometres (see Figure 6b). For both test environments, each route was visited twice with the surveyors in different seats and carriages. We used 4 different train companies to add more diversities to the dataset.

The first experiment assesses the spatial variation of the on-board magnetism. A surveyor sat in the same place and travelled through all of the above test routes. We then examine the resulting magnetic trajectory between every 2 consecutive stations on his journey. Our hypothesis is that all trajectories are non-stochastic or non-stationary (i.e. we want the magnetic field strengths within a trajectory to change significantly).



(a) East Dulwich - Peckham Rye route.
(b) Peckham Rye - Queens Road route.
(c) Queens Road - South Bermondsey route.
(d) Covent Garden - Holborn route.
(e) Old Street - Angel route.
(f) Waterloo - Southwark route.

Fig. 7. The autocorrelation plot of the test trajectories. The top row is overground ones, the bottom row is underground ones. We omit the remaining trajectories with a similar trend for page limit. The majority of autocorrelations are non zero, which confirms the non-stationary property of these magnetic time series.

Visually speaking, an autocorrelation plot of each trajectory time series has significant non-zero lags, which confirms the trajectory is non-stochastic. Additionally, the line segment's length gradually decreases below zero, which indicates a non-stationary time series (see Figure 7).

What surprised us the most when carrying out this experiment was that often when the train waited at the station, the magnetometer reported high measures without any movement from both the surveyor and the train. This phenomenon happened even at relatively quiet stations without many passengers on the platform. This ascertains our aforementioned assumption that electric-based trains greatly distort the on-board magnetic field. However, we discovered that not all carriages experienced the same effect (see Figure 8). This is a significant attribute for our system, since it combines with the natural magnetism distortion from nearby building structures to create a unique magnetic signature for each train carriage.

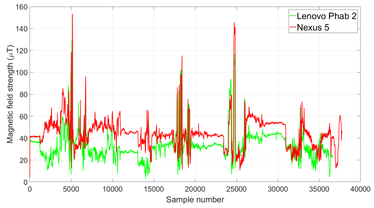
(a) Waiting at Stratford (overground) on Carriage #1.
(b) Waiting at Stratford (overground) on Carriage #4.
(c) Waiting at Holborn (underground) on Carriage #1.
(d) Waiting at Holborn (underground) on Carriage #3.

Fig. 8. The on-board magnetism readings from 2 different carriages on a static train. No movement from either surveyor or nearby passengers existed. This experiment proved the strong impact of the electric current from the railway structure on different train carriages.

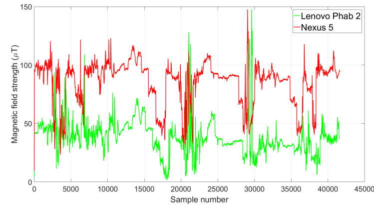
The second experiment assesses the magnetic field strength observed by people on the same carriage. Our hypothesis is that their mobile devices should capture similar magnetism readings. For each trip, two surveyors sat on the same carriage, albeit in different seats. The maximum distance between them was up to 7 metres. Figure 9 displays a remarkably similar shape of the two magnetic trajectories. The oscillation happened noticeably more often in the underground trips than the overground ones.

Thus far, we have used visual cues to reinforce the feasibility of using magnetism for co-location detection. The last experiment will inspect the accuracy of our automatic detection algorithm outlined in Section III. With our test scenarios, the two surveyors were always travelling on the same train, albeit in different carriages. Thus, for the sake of testing, we ignore the time-stamp of all non-co-located trajectories. So that our algorithm must examine all 702 possible pairs of overground trajectories and 1,190 pairs of underground ones. For each of Alice's trajectories, we compare it to all of Bob's. Our hypothesis is that our algorithm should only accept one of Bob's trajectories - the one that co-locates with Alice's.

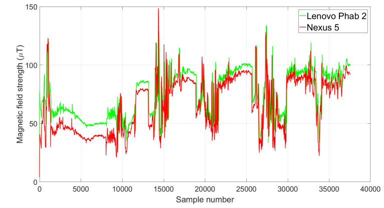
Out of all pairs of overground trajectories between Alice and Bob, our algorithm correctly identifies all 26 pairs that are indeed co-located. With these co-located pairs, the maximum DDTW score was only 3.8 and the maximum compressed rate was only 1.2. Recalling the heuristics that we defined earlier, these pairs of matching trajectories satisfied them with wide margins (see Figure 10). For the remaining 676 pairs of non-co-located ones, our algorithm comfortably rejected them based on just the DDTW score and the compressed



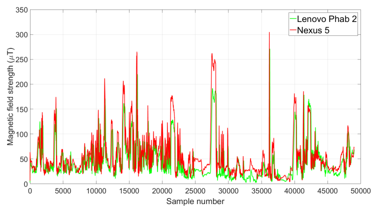
(a) East Dulwich - London Bridge route



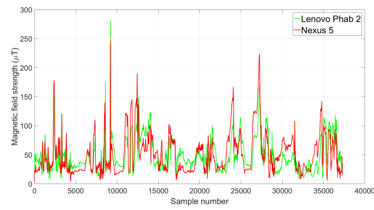
(b) Camden - Stratford route



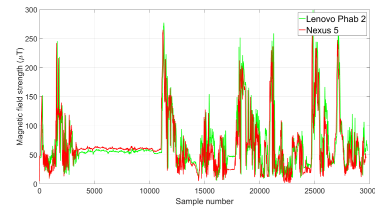
(c) Liverpool Street - Manor Park route



(d) London Bridge - Camden (Northern line)

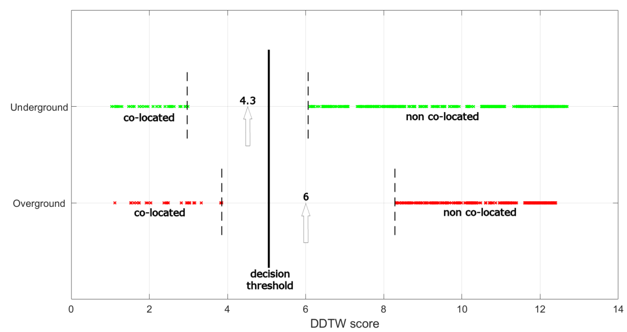


(e) Green Park - Canada Water (Jubilee line)

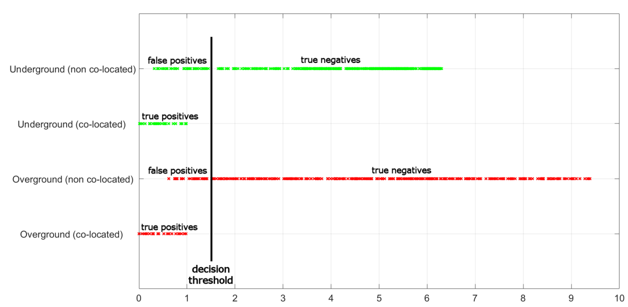


(f) Piccadilly - King's Cross (Piccadilly line). The flat line was caused by non-moving tube because of congestion near Leicester Square station.

Fig. 9. The magnetic field observed by two mobile devices on the same carriage. All test trips exhibit a remarkably similar shape. The gap in the magnitude was caused by slightly different sensitivities from different phone models. We only present 6 trips here due to page limit.



(a) The DDTW scores heuristic comfortably rejected all non co-located pairs with wide margins.



(b) The compress rate heuristic was based on the trajectory's length only, hence allowed some false positives.

Fig. 10. Validating the 702 pairs of overground trajectories and 1,190 pairs of underground ones. The compress rate heuristic responses much faster than the DDTW score heuristic, albeit allowing some false positives. Thus, we apply it first to get rid of the majority of the true negatives, then use the DDTW score to get rid of the remaining false positives.

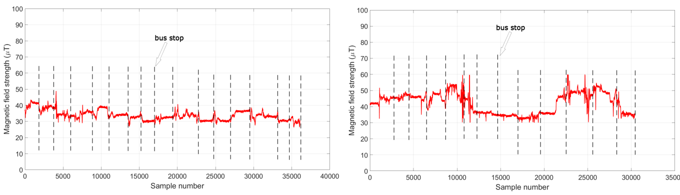
rate criteria. For these pairs, the minimum DDTW score was 8.2 and the maximum compressed rate was 9.4. A similar result was observed for the underground trajectories. Hence, our hypothesis holds for this experiment. It is worth noting that we deliberately ignored the time stamp constraint for this experiment. Realistically, this essential information will help getting rid of many pairs of trajectories which start at different times in the real-world.

B. Bus test environment

Our bus test scenario composes of 3 separate routes, which traverse 22 kilometres of travelling distance in the South-East and Central London (London Bridge - Old Street, Waterloo - Oxford Circus, Regent's Park - Angel), using 4 different buses (see Figure 11). On top of that, each bus may have an upper deck and a lower deck, which are equivalent to two train carriages. Through out this experiment, two surveyors sat on different seats on the bus in both decks.

Fig. 11. The heatmap of the bus test environment visualised on Google Maps. Regrettably, the magnetic distortion is almost non-existent.

Regrettably, a plot of the magnetism from all routes reveals little to no spatial variation. For instance, a 7 minute ride from Lancaster Place to Charing Cross, passing by 3 different stops had almost zero variation (see Figure 12). The highest magnetic distortion was just 80 μT which was observed right in front of Cannon Street station, compared to that of 350 μT for the underground test scenario and 210 μT for the overground test scenario.



(a) London Bridge - Old Street. (b) Waterloo - Oxford Circus.

Fig. 12. The magnetic field strength between consecutive bus stops. The magnetism variation was considerably less than the previous two train test scenarios. A relatively flat line was observed for different trajectories, which denied the chance to co-locate people on the buses.

These results draw up a conclusion that it is not feasible for co-location detection on the London buses using magnetism. An empirical explanation is that the London buses are hybrid diesel-electric vehicles. They use a diesel engine with electric storage through a lithium ion battery pack. As such, the vehicle itself does not alter the on-board magnetic field much. Additionally, the roads and pavements are a concrete mix of cement and sand which have zero impact on magnetism.

V. Related work

Since the essence of our paper is co-location detection for epidemic tracking, we will only overview other related work in the same area.

Kuk et al. detected carriage level co-location of people using just the accelerometer on the smartphone [3]. Their assumption is when the train starts moving, its coaches accelerate differently, which indicates whether two persons are in the same carriage. This is an interesting solution, albeit with two minor impracticalities. Firstly, many people rush onto the train at the beginning of their trip, and often pro-actively move to the door before the train reaches its destination. These unexpected movements add some biases to the accelerometer readings, which were not considered in their paper. Secondly, many trains are pre-programmed so that they accelerate and de-accelerate automatically, which makes it harder to differentiate passengers travelling simultaneously on different trains.

Some of the earliest work in epidemic tracking was from Eiko et al., for which a flu detection system was developed based on GPS and Bluetooth proximity detection [4]. This type of system actively monitors the user positions in real time, which is highly intrusive. Our approach is off-line based monitoring, where the users have full control of whether to upload their personal data for analysis. Additionally, we used low power sensors where Eiko et al. used high power sensors. Similarly, Farrahi et al. used Cellular mobile signal [5], whereas Nguyen et al. used the WiFi signals [6].

A non-physical detection approach was introduced by Lopes et al. [7]. They relied on the friendship and family ties reported through social networking databases to predict the disease spreading rate. Similarly, Huang et al. experimented the flu outbreak with Chinese social networking sites, using Dynamic Bayesian Network as the underlying algorithm [8].

VI. Conclusion and further work

Verifying if and when two persons are in contact is of paramount importance to contain a disease in an event of epidemic. We have presented an approach to detect co-location of people on the London public transports. The novelty of our work is the use of just low power magnetometer of the smartphone. No GPS, WiFi, Bluetooth or Cellular wireless signal is needed. We have assessed our proposal on the overground trains, the underground tubes and the buses. We discovered that people on different carriages experienced the magnetism differently at any moment, thanks to the electrified railway structure and the unique magnetic signature from the surroundings, which ascertains the feasibility of co-location detection on the trains and the tubes. The buses, on the other hand, did not yield much magnetism variation. To automate the matching process of the users' trajectories, we outlined 4 steps to smooth the raw data, extract the public transport related trajectories, highlight the pairs of matched trajectories across different users, and validate the matching pairs. The empirical results displayed a 100% successful detection ratio on our test environments.

Knowing whether two persons are co-located is not the end story. The longer they stay together, the more likely of being infectious the victim will be. Our next work shall incorporate this information to greatly enhance the usefulness of sensor-based epidemic tracking. At the end of the day, the users will voluntarily engage and contribute to the system, if it can be shown to benefit their healthcare.

References

[1] E. J. Keogh and M. J. Pazzani, "Derivative dynamic time warping," in *Proceedings of the 2001 SIAM International Conference on Data Mining*. SIAM, 2001, pp. 1–11.

[2] S. D. Dhingra, G. Nijhawan, and P. Pandit, "Isolated speech recognition using mfcc and dtw," *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, vol. 2, no. 8, pp. 4085–4092, 2013.

[3] S. Kuk, Y. Park, S. Han, and H. Kim, "Car-level co-location detection on trains for infectious disease epidemic monitoring," *Electronics Letters*, vol. 53, no. 1, pp. 8–10, 2016.

[4] E. Yoneki, "Fluphone study: Virtual disease spread using haggle," in *Proceedings of the 6th ACM Workshop on Challenged Networks*. ACM, 2011, pp. 65–66.

[5] K. Farrahi, R. Emonet, and M. Cebrian, "Epidemic contact tracing via communication traces," *PloS one*, vol. 9, no. 5, p. e95133, 2014.

[6] K. A. Nguyen, Z. Luo, and C. Watkins, "On the feasibility of using two mobile phones and wlan signal to detect co-location of two users for epidemic prediction," in *Progress in Location-Based Services 2014*. Springer, 2015, pp. 63–78.

[7] L. F. Lopes, J. Zamite, B. Tavares, F. Couto, F. Silva, and M. J. Silva, "Automated social network epidemic data collector," in *INForum informatics symposium. Lisboa*, 2009.

[8] J. Huang, H. Zhao, and J. Zhang, "Detecting flu transmission by social sensor in china," in *Green Computing and Communications (GreenCom), 2013 IEEE and Internet of Things (iThings/CPSCom), IEEE International Conference on and IEEE Cyber, Physical and Social Computing*. IEEE, 2013, pp. 1242–1247.