Privacy-Protecting COVID-19 Exposure Notification Based on Cluster Events*

Paul Syverson  
U.S. Naval Research Laboratory  
paul.syverson@nrl.navy.mil

Abstract

We provide a rough sketch of a simple system design for exposure notification of COVID-19 infections based on copresence at cluster events—locations and times where a threshold number of tested-positive (TP) individuals were present. Unlike other designs, such as DP3T or the Apple-Google exposure-notification system, this design does not track or notify based on detecting direct proximity to TP individuals.

The design makes use of existing or in-development tests for COVID-19 that are relatively cheap and return results in less than an hour, and that have high specificity but may have lower sensitivity. It also uses readily available location tracking for mobile phones and similar devices. It reports events at which TP individuals were present but does not link events with individuals or with other events in an individual’s history. Participating individuals are notified of detected cluster events. They can then compare these locally to their own location history. Detected cluster events can be publicized through public channels. Thus, individuals not participating in the reporting system can still be notified of exposure.

A proper security analysis is beyond the scope of this design sketch. We do, however, discuss resistance to various adversaries and attacks on privacy as well as false-reporting attacks.

The goal of this brief paper is to introduce the idea of, and contextual motivation for, using mobile phone location data from COVID-19 tested-positive (TP) individuals to identify cluster events and then to notify people of potential exposure simply by notifying them of cluster events. A sketch of a basic design to do this in a privacy-protecting manner is presented. We do not discuss even high-level particulars of necessary associated system features.

Existing privacy-protecting exposure-notification systems for COVID-19 infection generally do their detection and notification based on detected proximity to TP individuals [1][21][19]. Location information is typically not recorded by such systems. DP3T intentionally "avoids collecting location data, which is

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highly sensitive and very difficult to publish in a privacy-preserving way” [21]. While SafePaths explores adding GPS location information to proximity tracking [15], this is considered auxiliary to the primary task of identifying individuals who have been in close proximity to TP infectious individuals.

Deployed COVID-19 exposure-notification systems do employ location information. For example, the National Health Service of the United Kingdom (NHS) has set up a system whereby venues (pubs, hairdressers, village libraries, etc.) in England and Wales are required to obtain and post QR codes for patrons to scan when visiting. If the venue is later determined to be a COVID-19 hotspot, it is uploaded to a list that patrons can download and check against visited places scanned into their phones [11]. This is unlike our approach in multiple respects. It only works for fixed locations, which are locations of establishments of specific types. It requires participating locations to create and post QR codes. It only works for locations that individuals have scanned into their phones. And it identifies locations rather than events (locations at times).

Safe2 [18] is a mobile phone app that combines self assessment information about symptoms and proximity contact detection to provide a “Safe Score” indicating risk of infection ranging from “Healthy” to “Confirmed”. It also keeps track of location history, but shared in a privacy-protecting way somewhat similar to what we suggest below. Based on visited locations and contacts, an individual may be classified as a likely asymptomatic carrier. Notifications will then be sent to others who have been detected to be in close proximity to that individual, thus decreasing their Safe Scores.

The approaches and apps mentioned above by no means constitute a complete list, even ignoring the dynamic state of introduction and development of new apps. Nor do we provide more than a brief note of the features of the apps that we do mention as most relevant to or contrasting with our approach. For example, we have not otherwise mentioned PACT [17] or its incorporation in SafePaths. Buchanen et al. have produced a survey and analysis of privacy-preserving COVID-19 contact tracking that was relatively comprehensive at time of writing [3]. Landau’s recent book provides an introduction to the technology of contact tracing and its usefulness for public health, in which she discusses efficacy, equity, and privacy [11].

For Safe2 and the other privacy-protecting systems cited above, close proximity is determined by detected Bluetooth communication. Dehaye and Reardon have identified three attacks on Bluetooth-based proximity detection in the context of COVID-19 contact tracing apps [7]. The attacks require an adversary capable of placing a software development kit (SDK) in a moderately successful app, but Dehaye and Reardon argue that this is much easier than is usually assumed. See the paper for specifics. The good thing is that we need not accurately determine how hard such attacks are or how hard they are to counter if our exposure notification system does not depend on phones broadcasting proximity information. And specifics of COVID-19 infection patterns and COVID-19 testing technology may permit simplifications of privacy-protecting notifications based on presence at cluster events rather than directly detecting proximity to TP individuals.
First, unlike common influenzas and other familiar diseases, COVID-19 appears to have a high degree of clustering in its dispersion and to be spread more in events where infected individuals spend time in close proximity to groups of others. There are other dispersion clustering factors, such as whether gatherings are indoors and adequacy of ventilation, and clustering also occurs around some people who are individually linked to high number of infections. But generally, gatherings play a significant role in infection rates, whether or not they are exacerbated by other factors [10]. This includes both super-spreader large gatherings for social or cultural events as well as more moderate-sized gatherings [4].

Second, most tests for COVID-19 initially rolled out required specialized equipment to evaluate collected samples, required days or more to return results, were expensive, or all of the above. But analyses indicate that faster, cheaper point-of-care tests can be more effective at identification of infected individuals than more sensitive tests that are slower [13, 9]. And U.S. Department of Health and Human Services in partnership with the U.S. Department of Defense is now providing rapid point-of-care tests to communities across the United States [8]. Similarly, under the auspices of the World Health Organization, a global partnership has planned to make 120 million rapid tests available in low- and middle-income countries [23]. Analyses of effectiveness focus on identification and notification of infectious individuals. But coupled with dispersion patterns, another advantage of cheap, point-of-care tests emerges.

“[G]iven the huge numbers associated with these clusters, targeting them would be very effective in getting our transmission numbers down” [22]. Also, identifying a cluster does not require that everyone who was already infected at a particular event (location and time) has tested positive or even has been tested at all. As long as a sufficient number of TP individuals are associated with a given event, it is not important to identify which individuals were present, even pseudonymously, in order for the event to constitute a cluster. Since cluster events are indicators of risk of infection for all copresent at the event, informing individuals of those clustering events at which they were present is sufficient to notify them of potential exposure. And, individuals can make the determination of whether they were present at a clustering event entirely locally by having their phones compare clustering events about which they were notified with their location history.

Thus, we only need count the number of distinct TP individuals at an event to identify it as a cluster event. Like other privacy protecting COVID-19 notification systems, we can make use of anonyms (ephemeral pseudo-random identifiers) for each individual (where an individual is identified with the individual’s phone) at a given time. These can be combined with location data available to the phone, e.g, by GPS and other phone localization inputs, into an ordered pair, $(random_{ID}(i,t), location(random_{ID}(i,t),t))$.

Phones do typically have automatic access to location data but do not typically store location histories. Location histories are of course frequently tracked by third parties, and apps to track location history are readily available for the major mobile platforms. Also, privacy-protecting tracking and storing of mobile device location data for personal use has been studied since at least the
As noted above, the Safe2 app specifically stores and uses location history for COVID-19 exposure notification. And though Safe2 relies on Bluetooth and GPS, GPS alone can be effective at detecting useful COVID-clustering information. The specific means of localization is not central to our approach whether GPS, WiFi, Bluetooth, or other background signals (such as a scanned QR-code, as in the NHS app) as long as it is decoupled from the reporting of location history. As with other privacy-protecting aspects not novel in this design, we simply assume a privacy-protecting location history system and consider particulars out of scope for this paper.

If an individual tests positive, she submits such pairs for all times within a critical period, typically covering the maximum past interval during which she might have become infected. (Note that backward tracing of events appears to be more effective than forward tracing. Thus it is important to trace back to the time she might have become infected not merely the shorter period back to the time she might have become infectious.) Submission can be to a decentralized repository or to a centralized repository as long as the act of submission does not reveal association of submitted pairs. Given the limited goals of this paper, we simply assume such an association-protecting submission system. As an over-simple, somewhat concrete example of such a system, assume a centralized repository with submission protected by one or more mixes such that the output of the mixes is an unordered collection of all such pairs submitted during a given mix-system firing interval.

If notification of the results of a point-of-care test as well as notification of exposure are automated in a COVID-19 exposure notification app, and if adequate privacy protections are incorporated, then individuals have self-interested incentive to use the app even if its primary goal is to control spread. Nonetheless, as we shall see, the system can provide useful notification of exposure even to nonparticipants without an installed app.

**Malicious reporting of positive tests**

Another potential advantage of a cluster-event based approach is that, even without limiting TP reporting to authorized individuals, it provides automatic counters to the possibility that “people may falsely report they have been infected to cause mischief or to keep people home in order to shut down school or even to disrupt an election.” An individual falsely reporting a positive test cannot easily create such a result because they are unlikely to be the one to transition a location and time across the threshold of counting as a cluster event. And they cannot report at all for a location and time unless they were present at that event. More significant coordinated copresence or system hacking of location reporting would be required. And if coordinated copresence is the mechanism, then it may be that innocents who are notified because they were present at that cluster event should seek further testing and curtailing of social interactions.

Our cluster-event design thus automatically prevents, e.g., a student who is worried about his exam next week and anonymously reports a positive test
from thereby causing his school to shut down or his whole chemistry class to be forced into quarantine. A fan of one sports team cannot force a rival team into quarantine, etc.

A more substantial adversary, such as a nation-state, might be able to hack location histories for a phone, create sybils of phones at a location, etc. This could support an attack at a larger scale to disrupt a critical operation or degrade the availability of essential infrastructure or emergency personnel. Since the proposed design is meant to leverage rapid, point-of-care tests, it is also conducive to requiring input from authorized testing personnel at point of care to permit reporting a positive test. For example, an authorized TP code tied to a unique anonym bound to the identity of the mobile phone present when an individual is given the test could be sent at the same time test results are communicated to that phone, possibly even after the individual has left the point of care. And reporting of recent location history for that phone would require this authorization. Specifics of what capabilities such more significant adversaries might have and how all this would work is beyond the scope of this paper. We simply note here that the cluster-event approach remains compatible with requiring authorized parties to confirm TP status in order for reporting to occur. Obviously there is a tension between authorization mitigations against more powerful false reporting attacks and the ease and effectiveness of participation in the reporting and notification system. For example, without an authorization requirement, simple tests requiring no expertise to administer or evaluate can be made available and incorporated in the exposure notification system without an authorized-testing-personnel bottleneck. And a powerful adversary might include many other elements beyond our scope, such as compromising trusted authorization individuals, or the systems used for authorization, or the physical tests themselves. Lesser adversaries described above are still countered by the proposed system even without the authorization component. This is another advantage over any system that inherently has a trusted-authorization bottleneck.

Cluster event criteria

Submitted anonym pairs can be clustered into events according to latest understanding of what constitutes sufficient proximity in space and time to indicate risk of exposure likely enough to merit notification. Such clustering can be based simply on the number of copresent TP individuals. Further privacy preserving measures exist that would only reveal an uploaded location and time if a cluster event occurs there. Indeed there are deployed systems for large-scale gathering of data and release of associated statistics with guarantees of differential privacy [2].

With small thresholds of cluster events, however, even if the system only reveals locations if there is a cluster event, there may be a tension between revealing cluster events in a differentially private way while also not significantly affecting the rate of false negatives about clusters. This may not be a significant limitation, however. Without differential privacy, in principle an adversary
could submit a false positive result to enhance tracking of a TP individual. But this is not trivial. If, for example, the adversary had a device that could report from the individual’s location, easier tracking is available. So we would need to assuming knowledge of suspected trajectories followed by the targeted TP individual, and a hack of the location reporting system that doesn’t also make more straightforward tracking possible. In that case, the adversary could report TP locations and times along the suspected route to look for instances where the adversary’s report caused a cluster event. If so, and ignoring the entrance of other TP individuals causing the transition, the target’s presence could have caused locations-times to be at one less than the cluster-reporting threshold. These issues are also beyond the scope of this paper.

Exogenous information, if available, could affect clustering classification. For example, a location may have been separately identified as that of a salon, restaurant, house of worship, etc. This can affect what constitutes a notification-worthy cluster: two TP individuals copresent on a street corner in a city may be too low a threshold to classify this as a cluster event meriting notification, two TP individuals copresent in a poorly ventilated small salon might be a reasonable threshold, however.

Conversely, cluster locations that are identified simply by the number of copresent TP individuals but otherwise unknown and that are also responsible for large or repeated cluster events might be flagged for public health officials to investigate what is at that location and what sort of people are going there for what purposes.

On the other hand, unlike direct contact detecting approaches, since notification is only of cluster events, this approach cannot detect and therefore cannot notify people if they are exposed to a single copresent individual. As noted above, spread of COVID-19 is primarily through such clustering events, however. And this approach will also provide notification in a circumstance where an individual might never have come in close contact to anyone who tested positive (who is also participating in the detection/notification system) but was present at an event where multiple TP individuals were detected. So it not clear which approach is more likely to result in notification. Further, individuals from communities which have historically experienced disproportionate negative impacts of public health crises might be disinclined to participate in a contact tracing system [12]. Even if a non-participant, they might nonetheless self-interestedly check a public website for cluster events and act if they notice a significant cluster at an event where they (or loved ones) were known to be present. Recall that in any case, the primary goal is to produce notifications that lead to significant reduction in spread rather than to guarantee an individual of notification upon any exposure.

Relatedly, the approach allows different criteria for distance in making a clustering determination. As an oversimplified illustration, suppose a 2000 $m^2$ area is comprised of dozens of TP individuals where all individuals on the perimeter are within 2 meters of another TP individual for several minutes. The relevant cluster event for notification should probably cover the entire area at that time even if portions of the center are 10 meters from the nearest TP individual—
unless there is specific additional information that would exclude particular subareas. It may be likewise reasonable to include a larger area than just 2 meters beyond the perimeter for such a large cluster.

Another potential limitation of this approach is that it identifies a cluster as at one (possibly extended) location in a relatively brief time interval. It does not directly have a means to distinguish extended presence at a location of multiple TP individuals with few comings and goings over a period of hours (for example at a social gathering) versus a roughly persistent total of TP individuals resulting from regular turnover (for example, at a transit hub or commercial service establishment). This could matter for time of exposure to a particular individual as an indicator of infection risk likelihood. On the other hand, whether a notified individual learns of exposure at multiple cluster events at the same location based on either of these scenarios may not matter for the recommended course of action. Notified individuals are also more likely to know the circumstances of a particular succession of notified cluster events. And if they know the circumstances, they may be more prepared to notify others personally known to be associated with those circumstances, whether or not those others participate in or monitor the notification system.

Relatedly, there is no distinction made by the basic system of multiple exposures at a succession of locations versus prolonged exposure, e.g., during a shared ride in a car or mass transit vehicle. Again, it might not make a practical difference for purposes of the system whether this is identified as a single prolonged cluster event or succession of many shorter ones.

High-level Design Summary

1. Individual tests positive for COVID-19 and enters this in the notification app on their phone (alternatively notification of a positive result might be automated in a phone app and/or require input from a trusted testing official).

2. Individual’s phone app prepares a historical list of locations and times since the beginning of the critical period based on time of testing, each paired with a different random identifier.

3. Phone submits the list of pairs through a privacy preserving system.

4. System receiving these pairs from all reporting phones clusters them into events at which multiple TP individuals are present.

5. System pushes notifications of all cluster events to participants’ phones and/or posts these to a publicly accessible location, e.g., a website.

6. Notified individuals learn of exposures at cluster events.

The purpose of this brief paper is to introduce a novel concept of COVID-19 exposure notification based on creation of clustering events of which individuals are notified. We have simply assumed adequately privacy preserving systems for data gathering, processing, and publishing. And there are existing systems that
make this assumption plausible, some of which we have cited. Details matter, however, to the security, scalability, practicality, and usability of the overall system. Some of the details we have ignored include how submission of pairs unlinks submitting individuals from locations and histories of locations, the number of submitting individuals (in a region, during an interval), resistance to de-anonymization of location histories from plausible travel paths given a collection of location-time pairs, how long various data and information are held, etc. Clustering algorithms and clustering criteria are central to the cost, basic viability, and properties provided by this approach, but we have simply assumed these will be selected to function as needed. Cognizant of these assumptions, we have nonetheless identified a number of high-level properties of this approach, which we now summarize.

**Design Features**

- Does not depend on TP individual’s phone to have Bluetooth turned on in order to provide inputs.
- Does not depend on potentially exposed individuals to have Bluetooth on in order for system to find indications of exposure.
- Does not depend on direct physical interaction (Bluetooth or otherwise) between phones of TP individuals and exposed individuals.
- Exposure contact distance parameters do not depend on limitations of Bluetooth communication parameters.
- Does depend on availability of phone location history of reporting TP individuals.
- Does depend on phone location history (or human memory or...) for individuals to effectively make use of cluster event notifications or postings.
- Does reveal locations and times of cluster events, even small ones, which may identify particular households where there are multiple infections or that some sort of meeting took place at an otherwise nondescript location.
- Leverages fast test results, even if tests have only modest sensitivity.
- Depends on approximate numbers of TP individuals in cluster events rather than specific contacts with TP individuals.
- Cannot detect exposure to TP individuals outside of cluster events.
- Can notify of exposure even without close contact to a TP individual.
- Can notify of exposure even without participation as reporting individual.
- Counters false TP reporting and tolerates false TP reporting.
- Compatible with using trusted authorizations to counter false TP reporting by stronger adversaries.
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References

[1] Privacy-preserving contact tracing. https://covid19.apple.com/contacttracing, 02020.

[2] Andrea Bittau, Úlfar Erlingsson, Petros Maniatis, Ilya Mironov, Ananth Raghu Nathan, David Lie, Mitch Rudominer, Ushasree Kode, Julien Timnes, and Bernhard Seefeld. Prochlo: Strong privacy for analytics in the crowd. In Proceedings of the 26th Symposium on Operating Systems Principles (SOSP ’17), pages 441–459, 02017.

[3] William J Buchanan, Muhammad Ali Imran, Masood Ur-Rehman, Lei Zhang, Qammer H. Abbasi, Christos Chrysoulas, David Haynes, Nikolaos Pitropakis, and Pavlos Papadopoulos. Review and critical analysis of privacy-preserving infection tracking and contact tracing. Frontiers in Communications and Networks, December 8 02020.

[4] Muge Cevik, Julia Marcus, Caroline Buckee, and Tara Smith. SARS-CoV-2 transmission dynamics should inform policy. https://ssrn.com/abstract=3692807, September 14 02020.

[5] Lorrie Faith Cranor. Digital contact tracing may protect privacy, but it is unlikely to stop the pandemic. Communications of the ACM, 63(11):22–24, November 02020.

[6] George Danezis, Claudia Diaz, and Paul Syverson. Anonymous communication. In Burton Rosenberg, editor, Handbook of Financial Cryptography. CRC Press, 02010.

[7] Paul-Olivier Dehaye and Joel Reardon. Proximity tracing in an ecosystem of surveillance capitalism. In Proc. 19th Workshop on Privacy in the Electronic Society, WPES’20, pages 191–203. ACM, November 9 02020.

[8] COVID-19 rapid point-of-care test distribution. https://www.hhs.gov/coronavirus/testing/rapid-test-distribution/index.html, October 7 02020.

[9] Lee Kennedy-Shaffer, Michael Baym, and William Hanage. Perfect as the enemy of the good: Using low-sensitivity tests to mitigate SARS-CoV-2 outbreaks. https://dash.harvard.edu/handle/1/37363184, 02020.
[10] Sadamori Kojaku, Laurent Hébert-Dufresne, Enys Mones, Sune Lehmann, and Yong-Yeol Ahn. The effectiveness of backward contact tracing in networks. https://arxiv.org/abs/2005.02362, May 5 2020.

[11] Susan Landau. People Count: Contact-Tracing Apps and Public Health. MIT Press, April 2021.

[12] Susan Landau, Christy E. Lopez, and Laura Moy. The importance of equity in contact tracing. https://www.lawfareblog.com/importance-equity-contact-tracing, May 1 2020.

[13] Daniel B. Larremore, Bryan Wilder, Evan Lester, Soraya Shehata, James M. Burke, James A. Hay, Milind Tambe, Michael J. Mina, and Roy Parker. Test sensitivity is secondary to frequency and turnaround time for COVID-19 surveillance. medRxiv, 2020. https://www.medrxiv.org/content/early/2020/09/08/2020.06.22.20136309.full.pdf

[14] Create a coronavirus NHS QR code for your venue. https://www.gov.uk/create-coronavirus-qr-poster, 2020.

[15] Ramesh Raskar, Abhishek Singh, and Sam Zimmerman. Adding Location Context to Apple/Google Exposure Notification Bluetooth API: MIT SafePaths Encryption Proposals for GPS + Bluetooth, version 0.1. https://docs.google.com/document/d/1uTjdUetEEtwN-l6jw3HTZOdAd0kKaK7GR1YbdS10Ss/edit, April 26 2020.

[16] Michael G. Reed, Paul F. Syverson, and David M. Goldschlag. Protocols using anonymous connections: Mobile applications. In Security Protocols: 5th International Workshop, Paris France, April 7-9 1997, Proceedings, pages 13–23. Springer-Verlag, LNCS 1361, 01998.

[17] Ronald L. Rivest, Daniel J. Weitzner, Louise C. Ivers, Israel Soibelman, and Marc A. Zissman. PACT: Private automated contact tracing, mission and approach. https://pact.mit.edu/wp-content/uploads/2020/05/PACT-Mission-and-Approach-2020-05-19-.pdf, May 19 2020.

[18] Safe2: Frequently asked questions. https://safe2.org/faq/, 2020.

[19] SafePaths Alliance. Private kit: Safe paths; privacy-by-design. https://safepaths.mit.edu, 2020.

[20] Matteo Serafino, Higor S. Monteiro, Shaojun Luo, Saulo D. S. Reis, Carlos Igual, Antonio S. Lima Neto, Matías Travizano, José S. Andrade, and Hernán A. Makse. Superspreading k-cores at the center of COVID-19 pandemic persistence. medRxiv, 2020.
[21] Carmela Troncoso, Mathias Payer, Jean-Pierre Hubaux, Marcel Salathé, James Larus, Edouard Bugnion, Wouter Luks, Theresa Stadler, Apostolos Pyrgelis, Daniele Antonioli, Ludovic Barman, Sylvain Chatel, Kenneth Paterson, Srdjan Ćapkun, David Basin, Jan Beutel, Dennis Jackson, Marc Roeschlin, Patrick Leu, Bart Preneel, Nigel Smart, Aysajan Abidin, Seda Gürses, Michael Veale, Cas Cremers, Michael Backes, Nils Ole Tippetzhau, Reuben Binns, Ciro Cattuto, Alain Barrat, Dario Fiore, Manuel Barbosa, Rui Oliveira, and José Pereira. Decentralized privacy-preserving proximity tracing. [https://arxiv.org/abs/2005.12273], May 25 2020.

[22] Zeynep Tufekci. This overlooked variable is the key to the pandemic: It’s not R. The Atlantic, September 30 2020. [https://www.theatlantic.com/health/archive/2020/09/k-overlooked-variable-driving-pandemic/616548/].

[23] Global partnership to make available 120 million affordable, quality COVID-19 rapid tests for low- and middle-income countries. [https://www.who.int/news/item/28-09-2020-global-partnership-to-make-available-120-milion-affordable-quality-covid-19-rapid-tests-for-low-and-middle-income-countries], September 28 2020.