Privacy-Preserving Contact Tracing of COVID-19 Patients

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I. Introduction

The current COVID-19 pandemic shows that our modern globalized world can be heavily affected by a quickly spreading, highly infectious, deadly virus in a matter of weeks. It became apparent that manual contact tracing and quarantining of suspects can only be effective in the first days of the spread before the exponential growth overwhelms the health authorities (HA). Shutdowns of entire countries thus are a popular and drastic method to slow down infection rates in order to not overwhelm emergency capacities. While such shutdowns are effective, they also severely impact social and economical routines in the affected areas.

By automating tracing processes and quarantining everyone who came in contact with infected people, as well as arriving travelers, it should be possible to quickly loosen lockdown measures. Countries like China, Singapore and Israel hastily developed privacy-endangering schemes to computationally trace contacts using user-generated location histories or mass surveillance data [1]. There have been reports of de-anonymizations of infected South Korean citizens using the "anonymized" data set published by the state [2].

Citizen privacy is not a design goal in any of the known contact tracing schemes. While many countries require that infected people share their location history with the health authorities [3], it should not be required that everyone does. Nevertheless, society as a whole has an interest in resuming normal life as soon as possible. To approach this conflict of interests we propose a system for privacy-preserving contact tracing.

II. System Design

A. Secure multi-party computation

Secure multi-party computation (MPC) [4, Chapter 22] deals with creating protocols for joint computation on private, distributed data. It studies mechanisms to allow a group of n independent participants to collectively evaluate a function $y_1, \cdots, y_n = f(x_1, \cdots, x_n)$. Each participant holds a secret x_i, which shall remain hidden. The participants only learn their final result y_i, but not the input data of others. Any function f that is solvable in polynomial time can be represented as an MPC protocol [4, Chapter 22.2]. For our application we only consider two parties. We assume a semi-honest security model for the participants in our protocol. A semi-honest model can be reinforced to provide security in a malicious setting by accepting a performance penalty [5].

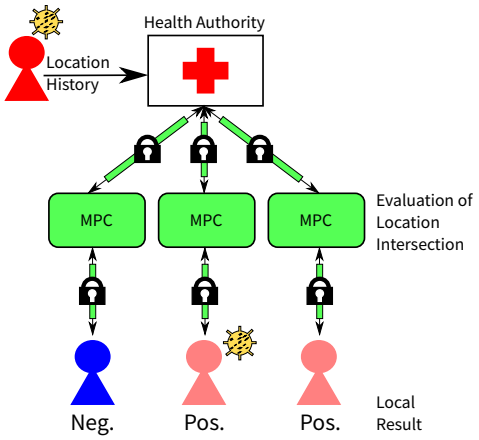

Fig. 1. An infected person shares their location data with the health authority. Three untested individuals starts separate MPC sessions with the HA. Note that not every positively evaluated contact is necessarily infected.

One way to realize a MPC protocol are *Yao's garbled circuits* [4]. Running an MPC protocol requires the one side to create a *circuit* from the function to be calculated and send it to the other party. The other side evaluates the circuit. Evaluation requires oblivious communication between both parties.

B. Contact Tracing with Secure Multiparty Computation

Our proposed system (see Figure 1) takes advantage on the existence of health authorities (HA) that are collecting location histories of infected users, as done in may courties hit by the epidemic [6]. We also assume that a vast majority of individuals use location-based services that store their history locally. The HA can use the data points of infected patients (and the associated timestamps) to initiate MPC sessions with everyone who wants to trace themselves. The HA creates a circuit which it will send to all interested individuals. During the evaluation, each individual has to perform oblivious communication with

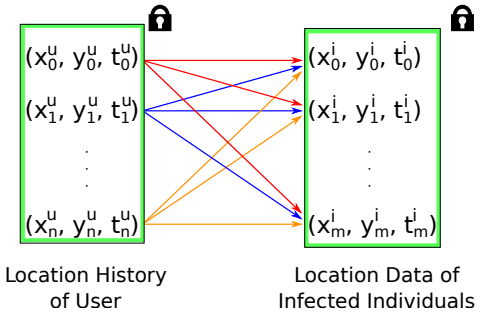

Fig. 2. For each user (u) location l_k^u the distance to all data points $l_0^i, \ldots, l_m^i$ of infected people i has to be calculated. If the distance is smaller than a certain threshold, then the user can have possibly been infected.

the HA. Together, the parties determine where trajectories of infected and non-infected people intersect. Contact tracing is done in private so that only the traced individual can learn their status. No information about past locations of infected people or users of the system is revealed to either side.

C. Contact Tracing Algorithm

MPC allows inputs and outputs to remain hidden from other parties. Input locations $l_k := (x_k, y_k, t_k)$ consist of geographical coordinates and a temporal component. Each user u has n to-be-checked locations in their location history. For a location l_k^u MPC is used to calculate the Euclidean distance to all data points $l_0^i, \ldots, l_m^i$ from the data set of infected people. If the distance is smaller than a certain threshold and if timestamps are close, then the user can have possibly contracted the virus. For a visualization of this process see Figure 2. Only the user herself will learn the final result.

Optimizing secure nearest neighbour queries and proximity search remains an open research question [7], [8]. The algorithm described above is guaranteed to not leak more information than the ideal functionality to either side.

D. Performance Considerations

The contact tracing algorithm requires $\mathcal{O}(n \cdot m)$ computation and communication per user. Here, m is the number of data points stored at the HA, so it remains constant until new cases are discovered. The number n of locations in the user's history can be highly variable. On a computer with an Intel(R) Core(TM) i7-8565U CPU @ 1.80GHz and 16 GB RAM, using the Semi2k Protocol from MP-SPDZ [9] and $n = m = 20$, the execution required 37.54 ± 3.74 seconds (standard deviation). We are confident that the execution time can be reduced significantly and that scalability can be improved by further investigating the following ideas.

Recent work done by Chen et al. proposes a secure algorithm for finding k-nearest neighbours [7]. Their algorithm runs in sublinear time, leveraging both MPC and *homomorphic encryption*. Future work on our system includes integrating the algorithm of Chen et al. to improve performance.

Further enhancements could consist of preprocessing data to identify disjoint regions. The HA could provide data sets based on state or city level, allowing performance improvements with minimal privacy loss. People often remain in the same location for extended periods of time (e. g., at their home), especially during social distancing. Such a trajectory consists of a large number of points with only little new information. These data points could be clustered during preprocessing into a single location with a radius and time range.

E. Decentralization

Our proposed system uses a central party (the HA) for contact tracing. Each person who wishes to check their own history for contact points with infected people has to go through this central instance. Theoretically, a malicious HA could induce a movement of panic by tailoring additional locations as contact points. Withholding real contact points is also a possibility for the HA to touch up statistics. However, both of these attacks would not be helpful for reaching the overall target of tackling a pandemic situation, which is why we assume a semi-honest HA.

A fully distributed approach would require for every infected person to offer each checking individual a session of our protocol. An infected patient would have to provide large amounts of computational and network resources to securely communicate their location history with users of the system.

An alternative approach to contact tracing currently used by the Singapore Ministry of Health [1], [2] is to use Bluetooth and Wifi sensing. With the idea of Altuwaiyan et al. [10] it is possible to compare a set of observed devices to a set of devices belonging to infected individuals. In contrast to our proposal, this approach requires that every participant has their radio interface activated at all times.

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