Blockchain Driven Privacy Preserving Contact Tracing Framework in COVID-19

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Abstract—Contact tracing has been proven an effective approach to mitigate the virus spread in pandemics like COVID-19. As an emerging powerful decentralized data sharing and storage technique, blockchain has been explored to ensure data privacy and security in contact tracing processes. Existing work mostly treats blockchain as a separate storage system requiring third-party servers to perform data collection and computation, and avoids revealing detailed interior design of blockchain storage. However, blockchain system is capable to work as a fully automatic distributed contact tracing system without any third-party server by tackling the following challenges: 1) how to ensure the contact tracing correctness without compromising privacy; 2) how to design efficient and effective consensus mechanism to ensure the system security and robustness; 3) how to design an incentive mechanism to motivate people to behave honestly. In this article, we present the Blockchain Based Contact Tracing Framework for the contact tracing problem. In the framework, RSA encryption based transaction verification algorithm (RSA-TV A) is proposed to ensure contact tracing correctness, which can achieve more than 97% contact case recording accuracy even when each person has 60% chance of failing to verify the contact information. Reputation Corrected Delegated Proof of Stack (RC-DPoS) consensus mechanism is applied to jointly work with the proposed incentive mechanism, which can ensure timeliness of reporting contact cases and meanwhile balance the reward gained by different people. A novel contact tracing simulation environment is created in the simulation part, which considers three different contact scenarios. The simulation results demonstrate the effectiveness, robustness and attack resistance of RSA-TV A and RC-DPoS in the proposed Blockchain Based Contact Tracing Framework.

Index Terms—Blockchain, COVID-19, Consensus Mechanism, Contact Tracing, RSA

I. INTRODUCTION

Since the first case of the novel corona-virus COVID-19 discovered in Wuhan, China in December 2019, there have been over 293 million globally confirmed cases of COVID-19, including 5 million deaths by January 2022. The variants of COVID-19 keep emerging, making the situation worse and unpredictable, and have brought considerable degree of fear, emotional stress and anxiety among individuals around the world. The virus causes severe acute respiratory infection, bringing symptoms such as cough, fever, fatigue and breathlessness, which is very similar to symptoms caused by regular influenza. The high contagiousness makes it hard to control the virus spread. In order to ensure people who contacted with the patient get informed timely and receive medical treatment as soon as possible, it is imperative to record the past contact trajectories of the patients.

Many countries have developed methods to trace the contact history of patients, such as Trace Together in Singapore and the QR code System in China. Some technology companies also developed contact tracing tools, such as Google and Apple developed a Bluetooth based API that can be used by third parties to develop apps. These apps mostly use Bluetooth to recognize nearby devices or GPS signal to get the accurate location to achieve contact tracing. Most of these tracing systems rely on a central server controlled by governments or healthcare authorities, which may collect the users’ contact histories, identities and even privacy data through an app installed on smart phones. According to the survey at multiple countries in, though most people accept app-based tracing methods, the concern about the security and privacy is still an obstacle to the common adoption of tracing apps in some countries, for example German and US. A centralized server based system usually suffers single-point failure and is weak to attacks. Decentralized contact tracing methods are then promoted, which give more control to users. In decentralized model, users are not required to update all data to the server. They can hold data locally, and share their data when necessary. The server will notify users who may potentially have contacted with positive cases.

As an emerging decentralized data creating, sharing and storing technique, blockchain system is introduced into contact tracing systems to promote the security and privacy. Blockchain stores data into blocks that are connected to each other as a chain. The data stored in blocks are not able to tempered. Smart contract deployed on blockchain can perform various functionalities. Furthermore, encryption and anonymization technologies can be applied in blockchain system to protect user’s identity. The consensus mechanism in Blockchain allows blockchain systems keep working stably without a central server.

The main challenges to develop a blockchain-based contact tracing methods are from four overlapped aspects: 1) Instead of simply treating blockchain as a separated storage method, how to leverage powerful consensus mechanism in blockchain system to promote data security; 2) How to design an effective consensus mechanism to organize data storage and meanwhile achieve low latency of recording contact information. The popular consensus mechanisms are usually too computational expensive for mobile devices, and may bring significant delay of recording contact information. People should be able to check the stored contact record timely to prevent further possible virus spread. 3) How to design the incentive mechanism...
so that people are motivated to join the contact tracing system and behave honestly. 4) Due to lack of real-world contact data, as well as high cost of testing whole system in practice, it is hard to evaluate the effectiveness and efficiency of whole systems. The difficulty of collecting real-world contact information, is not only from privacy concerns, but also diversity of people contact scenarios. For example, some people may live in cities where contact can easily happen, while some people living in rural areas are not usually gathering around. Some people’s job may require meeting people face to face every day, while some people can work remotely at home to avoid contact. This diversity also makes it hard to design incentive mechanism fair to every one.

Existing literatures have developed many contact tracing systems using blockchain technologies. [6] propose proof of location and develop smart contracts to ensure the privacy of contact list. However, no simulation is provided, and the efficiency is not demonstrated. In addition, there is no incentive mechanism to motivate users to join the system. They just assume there are plenty of users in the system behaving honestly, while the situation is hard to achieve in practice. [7] propose BeepTrace blockchain-based contact tracing solution, where a blockchain system plays the neutral role in bridging data transmission between different parties, such as patients, doctors and government authorities. The users’ geodata are securely preserved in specially designed blockchain address architecture, and the contact history can be derived from the geodata stored in blockchain. However, the efficiency of this system is not demonstrated, and no specific consensus mechanism and incentive mechanism are specified in the paper. Therefore, the contact tracing accuracy and timeliness are hard to be evaluated.

There is seldom work that clearly addressed all above mentioned 4 challenges, leaving doubts about implementation details in the system and how the system work in real-world scenarios.

In this article, we propose a fully third-party-free contact tracing framework based on blockchain system. A RSA based transaction verification algorithm is proposed to ensure the correctness of recorded contact information and to improve resistance to system failure. To efficiently store transactions into blocks, we propose Reputation Corrected Delegate Proof of Stack (RC-DPoS) consensus mechanism, which can control the right of appending new blocks. An incentive mechanism is then designed to work with RC-DPoS to motivate people to join the system and behave honestly. Finally, we design a contact tracing simulation method that simulates different real-world people contact scenarios to evaluate the effectiveness of proposed framework.

The reminder of this article is organized as follows. In Section II we discuss existing related works of contact tracing. Section III is dedicated to presenting the overview of proposed contact tracing framework. Next we elaborate detailed design of transaction verification algorithm, RC-DPoS and incentive mechanism in Section IV, Section V and Section VI respectively. Simulation is conducted in Section VII and Section VIII concludes the paper.

II. RELATED WORK

A. Contact Tracing

Contact tracing refers to the process that records the people contact history so that the people contacted with a patient can be informed and get medical treatment as soon as possible. The World Health Organization (WHO) has stressed the importance of contact tracing since EBOLA break in 2014 (8).

Various contact tracing tools have been developed using location technologies such as GPS, WiFi, cell phone signal and Bluetooth (9, 10, 11, 12, 13, 14).

[15] propose a centralized contact tracing method, which assumes every user has their location history stored in their devices, and the health authority is able to read the data. [11] propose to use call data record to trace the patient once she/he is diagnosed positive. However, the trace build is not practical since most people answer several calls at very limited numbers of phone number, therefore we can only get limited number of locations.

The contact tracing system based on GPS signal are not reliable for in-door situations, while in-door contact is one major way of virus spread due to close distance and long exposure time. [12], [9], [10] propose to use WiFi or wireless access points to discover contact cases. These frameworks require users to connect their devices to specific wireless access points, however, in some public areas such as shopping malls, airports and train stations, people may not join public WiFi due to network security concerns. Bluetooth technology can scan nearby devices and get devices identity in a small range, which can help generate the contact cases ([14]). In this article, we also leverage this advantage to protect users privacy that records users contact history without disclosing users’ real identities and specific location.

[16] propose PACT protocol, where every user holds the contact tracing data on their own local devices, and only when they are tested positive, they will broadcast their contact information to a public platform. Every other user will check the list on the platform to confirm if they have any contact with anyone in that list. Though this protocol is a third-party-free mobile contracting protocol and easy to be implemented in practice, it is very weak to malicious attacks. The users are not guaranteed to behave well, and the public platform is easy to be tempered since it is open to anyone.

Most of existing works are centralized where there is a third-party server collecting all the user’s personal data and contact history data to match contact records ([17]). Centralized models expose risk of single point failure, privacy data leaking and security compromising. Though some contact tracing methods are proposed to be decentralized ([13], [16]), these methods still require a server to process functions such as notification, and are vulnerable to dishonest behaviours from malicious users.

B. Blockchain

Blockchain technology is first proposed by [19] as a decentralized ledger for Bitcoin system, which ensures data security without any trust given to third parties. Blockchain system constructs a peer-to-peer network, where each user
plays exactly the same role, and follows the same protocol. Every user stores a whole copy of blockchain, so that all the data on the blockchain is extremely hard to be tempered and single-point failure can also be avoided. There’s no need for a central server to perform functions in the system, such as collecting, computing or storing data. Users have exactly the equal right to perform functionalities by executing smart contracts deployed in the system. A consensus mechanism is enforced in the system to control which user is qualified to generate a new block at each step. An incentive mechanism is also important in the system to motivate users to compete for the right of generating a block.

Blockchain technique can make a system work stably without any trust among parties. With some anonymity techniques and data encryption techniques, users in a blockchain system can share data securely without compromising privacy. Blockchain has demonstrated applicable scenarios using IoT devices with low-computational power after mitigating computation complexity of blockchain system ([20], [21], [22], [23], [24]).

Though there are challenges, Blockchain technique shows great potential for developing privacy preserving and efficient contact tracing applications ([25], [26]) point out several challenges and risk associated with the available contact tracing apps and analyze how the adoption of a blockchain-based decentralized network can could provide users with privacy-preserving contact tracing without compromising performance and efficiency.

Besides the BeepTrace ([7]) mentioned above, there exist many other blockchain-based contract tracing frameworks or systems. ([27]) propose a high-level blockchain based contract tracing framework where blockchain is used for patients to publish contact list. [28] propose PTBM leveraging both permissionless and permissioned blockchain to manage users’ location data, and 5G technique provides support for low latency communication. In PTBM, authorized third parties, like medical center and medical organization, are able to compute the context history and publish history route of patients.

[29] propose $P^2B$, where users can upload contact information to blockchain storage to be further verified and cross-checked by clients and authorities. $P^2B$ is demonstrated with higher data transmission efficiency than BeepTrace. [30] propose a three-tier architecture solution for storing numerous data collected by Internet-of-MedicalThings (IoMT) for contact tracing, where blockchain was employed to securely transfer the data from the infected person to the hospital system using the edge infrastructure.

[31] consider a sixth-generation (6G)-assisted unmanned aerial vehicles (UAVs) en-powered mass surveillance system in dense areas, which can monitor body temperature of persons with thermal imaging sensors. Blockchain also works as storage system in the proposed framework, and with the powerful bandwidth of 6G, the data can be processed with low latency. [32] consider in-door contact tracing scenarios, and propose TB-ICT contact tracing framework, where dynamic Proof of Work (dPoW) credit-based consensus algorithm coupled with Randomized Hash Window (W-Hash) and dynamic Proof of Credit (dPoC) mechanisms are proposed to differentiate between honest and dishonest nodes. TB-ICT can motivate people to behave honestly since better credit can decrease mining difficulty. But PoW-based consensus mechanism may bring high computation overhead while BLE-carried devices adopted in the system are not usually computational powerful.

III. CONTRACT TRACING FRAMEWORK OVERVIEW

A. Preliminary Settings

In this paper, we assume our contact tracing system will be deployed through clients on smart devices. People can join the contact tracing system by installing the client on their smart devices. It is assumed each user carries one device with the client installed. The client will generate private-public key pair and a unique pseudo device ID for each device. The client will use Bluetooth to share the pseudo device ID of current device as well as getting pseudo device IDs of other nearby devices. The Bluetooth technique is considered suitable for the contact tracing framework specified in this paper, since we directly record the pseudo device IDs of contacts rather than record accurate GPS coordinates and match contact information afterwards. With no accurate location recorded, privacy will be preserved. In addition, Bluetooth is capable to evaluate the distance between two devices within a certain range by the strength of Bluetooth signal. Therefore, the contact distance can be easily computed ([33]). The furthest contact distance considered in this paper is 5 meters where Bluetooth can produce strong enough signal to support accurate computation.

The client on a device will record all the pseudo device IDs of nearby devices within a range. This process is fast and secure since the client only scans surrounding devices without having to establish connection to them which avoids cyberattack through Bluetooth channel. If a device is detected within 2 meters, the client will identify this as a contact case. The client will then store the pseudo device IDs of contacted devices into contact list locally in a special format which will be specified in next section.

Most of previous works ignore the fact that mobile devices are not as stable as computers in terms of internet connectivity, system robustness and security level. The device may fail to collect the contacted device info, or be attacked to record false contact list. To improve the data integrity, a special role witness is proposed in this paper. All the devices that are 2 meters away but still within 5 meters from the current device are considered witnesses of the contact case. Witnesses play important roles in the proposed tracing framework, which could help verify the reported contact list, speed up the verification process, and recover the missed contacts. The client will also store the pseudo device IDs of witnessed devices into witness list locally in the similar format as contact list. With the pseudo IDs of contact devices and witness devices stored locally, users can check whom they have contacted with and who are witnessed by them at any time without knowing the real identity of the device owner.

B. Contact Tracing Procedure

Based on the above setting, we now illustrate the whole Blockchain-Based Contact Tracing Framework in Figure [1]
the figure, at a given Timestamp, assume user $u_1$ would like to report his current contact case. He will initiate a contact tracing transaction $T_{con}$. Let’s assume users $u_2$ and $u_3$ are within 2 meters from $u_1$, and considered to have contact with user $u_1$. Users $u_4$ and $u_5$ are 2 meters away but still within 5 meters from $u_1$, and they witness that $u_1$ is with $u_2$ and $u_3$. There are generally 6 steps from generating contact record as blockchain transaction to the transaction being stored to blockchain storage in every device.

**Step 1:** User $u_1$ initiates a blockchain transaction $T_{con} = \{T_{id}, u_1, ContactList, WitnessList, Timestamp\}$, which is used to record the contacted people (devices) at timestamp Timestamp. One transaction represents one contact case of users at some timestamp. $T_{id}$ is an unique transaction ID for each transaction. The ContactList and WitnessList contains encrypted message from $u_1$ encrypted by the public keys of each contacted devices or witness devices. We defer the formal definition of ContactList and WitnessList to Section IV. Timestamp is the exact time that $u_1$ contacts the users in ContactList.

**Step 2:** User $u_1$ then broadcasts the transaction $T_{con}$, through internet to every user who have the client installed. Since no one knows others’ identities, $u_1$ is not able to directly send message to $u_2$, $u_3$, $u_4$ and $u_5$.

**Step 3:** When each user receives transaction $T_{con}$, it will check if it contacted or witnessed $u_1$. Then the contacted users, $u_2$ and $u_3$ in this example, and the witnessed users, $u_4$ and $u_5$, will try decode the received message, sign the decoded message and broadcast this signed transaction. Then transaction generator $u_1$ will receive the signed transaction.

**Step 4:** After receiving the signed transaction $T_{con}$, $u_1$ will check the signature by decoding the signature with contact’s or witness’s public key to make sure the contact list and witness list are signed by right person. $u_1$ will wait for the signatures within a specific delay $d$, such as 60 minutes. The full list of ContactList is considered valid if all the tuples in ContactList are signed by correct persons, or at least one witness confirm that ContactList is valid by signing the corresponding tuple in WitnessList. If still not all contact records are confirmed within $d$, $u_1$ will only preserve the signed ones, and put filtered transaction $T_{con}$ into a shared transaction pool which is synchronized on every device along with blockchain.

**Step 5:** With some given frequency, one of the candidate miners will be selected (randomly or according to other mechanisms) to pack all the transactions in the transaction pool into a block. In this paper, we propose the Reputation-Corrected DPoS (RC-DPoS) mechanism to choose the candidate miners, which will be introduced in detail in Section V.

**Step 6:** The block is finally appended to the blockchain by the miner, and broadcast to all users in the network for synchronizing.

Steps 1 to 4 will be elaborated in Section IV by proposing RSA-Based transaction verification algorithm. In Section V RC-DPoS and corresponding incentive mechanism are presented to complete Step 5 and Step 6.

IV. TRANSACTION VERIFICATION ALGORITHM

In this section, we will first describe how to initialize credential for each user and then present **RSA-based Transaction Verification Algorithm** (RSA-TV A) algorithm. There are two major concerns about contact tracing system: 1) data integrity: the collected contact data is complete, tamper-proof and correct; and 2) privacy: the whole system cannot disclose any location or identity information of users. In this paper, We propose **RSA-based Transaction Verification Algorithm** (RSA-TV A)
to make sure the contact records in the transaction are valid meanwhile ensuring the anonymity of the whole system.

We employee RSA algorithm as encryption module \( \text{(RSA)} \). RSA algorithm is an asymmetric encryption algorithm, and is able to generate a key pair, (public key, private key) for a user. Public key is known by public, while the private key is only known by the user. The secret text encrypted by public key can only be decoded by private key holder. A document can be signed by private key indicating owner’s consent to the document, and the signed document can be verified by user’s public key to ensure the signature is indeed signed by the private key owner.

Next we will first describe how to initialize credential for each user and then present RSA-TV.

A. Generate User Credential

When a user \( u \) installs the tracing client on a smart device, the client will first name the device with an unique device id, denoted as \( u_DID \), and then generate a RSA key pair (public key, private key), denoted as \( (u_{\text{pub}} \_\text{key}, u_{\text{pri}} \_\text{key}) \). The length of each key is set to 1024 bits. The private key will be stored locally in the user’s device. The public key and the device information will be included in a transaction by the user, and then be mined into blockchain by miner. This transaction is called “Registration Transaction”, and is defined as \( T_{\text{reg}} \equiv \{T_{\text{id}}, \{u_{\text{DID}}, u_{\text{pub}} \_\text{key}, t\}\} \). \( T_{\text{id}} \) is the unique id for each transaction and is generated based on timestamp \( t \) and the transaction content \( \{u_{\text{DID}}, u_{\text{pub}} \_\text{key}, t\} \), so that any change made on the content will bring a definitely different \( T_{\text{id}} \).

When the registration transaction is stored in the blockchain, since every user in the system have a local copy of the whole blockchain, each of them will hold the public keys for every others. Every user is able to modify his device id or public key, but he needs to resubmit a new “Registration Transaction”, so that every other users in the system can get a new copy of his device id or public key.

Users will scan the nearby devices (through Bluetooth) with a given frequency, to get the nearby devices’ IDs and record them locally. We avoid any device connection through Bluetooth to ensure security. The client will only collect the devices’ IDs, and look up the registration transactions to get the public keys for generating secret message later used in ContactList or WitnessList. Now if the user wants to verify contact history and store the contact information into Blockchain storage, he will need to generate a “Contact Transaction”, and invoke the proposed transaction verification Algorithm.

B. RSA-based Transaction Verification Algorithm (RSA-TV)

If there are nearby devices scanned with Bluetooth, any user \( u \) can generate “Contact Transaction”, denoted as \( T_{\text{con}} \equiv \{T_{\text{id}}, \{u_{\text{DID}}, C, W, t\}\} \), where \( T_{\text{id}} \) is the unique id for each transaction and is generated based on timestamp \( t \) and the transaction content \( \{u_{\text{DID}}, C, W, t\} \). The \( u_{\text{DID}} \) is the device ID of \( u \), and \( t \) is the timestamp for this contact case. \( C \) and \( W \) are Contact List and Witness List, respectively, which contain the information of the contacted people/devices and the witness of this contact case. To generate \( C \) and \( W \), user \( u \) first needs decide the original secret text \( \text{Org} \_\text{Text} \), and then encrypt it with the public key of the contacted people (e.g., \( u_i \)) and the witness (e.g., \( u_j \)) of this contact case to generate encrypted texts \( u_{\text{pub}} \_\text{key} \_\text{EncryptedText} \) and \( u_{\text{pub}} \_\text{key} \_\text{EncryptedText} \), respectively. Formally, the Contact List \( C \) is defined as a set or tuple: \( C = \{(u_{\text{pub}} \_\text{key}, u_{\text{pub}} \_\text{key} \_\text{EncryptedText}) | u_i \text{ contacted with } u \text{ at } t \} \). Similarly, the Witness List is defined as: \( W = \{(u_{\text{pub}} \_\text{key}, u_{\text{pub}} \_\text{key} \_\text{EncryptedText}) | u_j \text{ witnessed } C \text{ at } t \} \). Witness List can be very helpful to avoid contact list lost and dishonest user behaviors. We will show this later in Section \( \text{VI} \). The transaction \( T_{\text{con}} \) will then be broadcast to all users in order to protect privacy. Each user will check if \( C \) or \( W \) in the received \( T_{\text{con}} \) contains his/her public key. If so, the transaction requires verification. Since the text are all encrypted, therefore only the user who holds the public key can decrypt the text encrypted by his public key.

When \( u_i \) identifies the tuple \( (u_{\text{pub}} \_\text{key}, u_{\text{pub}} \_\text{key} \_\text{EncryptedText}) \) in a transaction \( T_{\text{con}} \) generated by \( u \), he will decode the encrypted text \( u_{\text{pub}} \_\text{key} \_\text{EncryptedText} \) with his private key \( u_{\text{pri}} \_\text{key} \) to get the original text \( \text{Org} \_\text{Text} \). Then \( u_i \) will check his local contact history or witness history. If \( u_i \) has the record that he contacted with \( u \) or witnessed contact list \( C \) at timestamp \( t \pm 3 \) min, then \( u_i \) can confirm the tuple \( (u_{\text{pub}} \_\text{key}, u_{\text{pub}} \_\text{key} \_\text{EncryptedText}) \) in \( T_{\text{con}} \). Then \( u_i \) needs to send a message back to \( u \) to indicate that the contact record about \( u_i \) in \( T_{\text{con}} \) is confirmed by him. Specifically, \( u_i \) signs the original text \( \text{Org} \_\text{Text} \) with his private key. The signed text is denoted as \( u_{\text{pri}} \_\text{key} \_\text{SignedText} \). Then \( u_i \) replaces \( (u_{\text{pub}} \_\text{key}, u_{\text{pub}} \_\text{key} \_\text{EncryptedText}) \) with \( (u_{\text{pub}} \_\text{key}, u_{\text{pri}} \_\text{key} \_\text{SignedText}) \) in \( T_{\text{con}} \), and broadcast to all users. If \( u_i \) can not find record that he contacted with \( u \) at timestamp \( t \pm 3 \) min, then \( u_i \) believes this is a wrong record. \( u_i \) will sign the \( \text{Warning} \_\text{Text} \) = “Wrong Record” instead of signing the original text \( \text{Org} \_\text{Text} \). The tuple \( (u_{\text{pub}} \_\text{key}, u_{\text{pub}} \_\text{key} \_\text{EncryptedText}) \) in \( T_{\text{con}} \) will then be \( (u_{\text{pub}} \_\text{key}, u_{\text{pri}} \_\text{key} \_\text{SignedWarningText}) \). Once \( u \) receives the updated \( T_{\text{con}} \) from user \( u_i \), \( u \) will verify the signature with the public key of \( u_i \).

The contact list \( C \) in \( T_{\text{con}} \) is considered fully verified if: 1) there is no signed warning text in any tuples in \( T_{\text{con}} \), and 2) all the tuples in \( C \) are signed by correct user or at least one tuple in \( W \) is signed by witness since we consider the witness saw this contact case. If only part of the contact list \( C \) are verified within a specific delay \( d \), only the verified correct tuples in \( C \) will be preserved in \( T'_{\text{con}} \). The transaction \( T'_{\text{con}} \) will be put into the shared transaction pool waiting to be mined, e.g. permanently stored in blocks. Then both transaction generator \( u \) and verifier \( u_i \) in \( T_{\text{con}} \) will get rewards. We will discuss reward policies in Section \( \text{VI} \). Figure \( \text{VI} \) shows an example of RSA-TV.
Though it seems more straightforward to directly broadcast the verified transactions to all users without a miner, we introduce miners for two reasons: 1) Users are rewarded for reporting contact information. However, people have different chance to have contact cases due to variety of jobs or activities. People who live or work in human-dense areas, such as cashiers in markets and staffs of transport stations, will obviously gather more reward than those who stay at home. This will further encourage people to go out and make contacts in order to earn rewards, which is against the avoiding contact policy during pandemics. The existence of miners allows those who don’t have much contacts to have more chances to earn rewards. If we set appropriate reward policies for mining, people can be encouraged to stay at home to earn reward. 2) Since miners can be the one not in the Contactlist or WitnessList, it helps avoid group cheating that small groups deliberately generate contact cases, and verify contact transactions for each other in order to gather great amount of reward rapidly. Therefore, miners can improve the security level of the whole system.

The Delegated Proof of Stack (DPoS) consensus mechanism ([35]) is a popular light-weight consensus mechanism to decide miners in a blockchain system. DPoS can provide high-speed consensus making so that emerging transactions can be stored into blocks timely. In DPoS consensus mechanism, each user holds some stacks, which are usually crypto-currency. At each round, each user will vote someone he trust to be a miner, and the weight of the vote is proportional to the stack of the voter. That is, more crypto-currencies brings hihger weights to the vote. After the voting, the users with top $k$ total weighted votes will be selected as $k$ candidate miners. Each time when a
block is needed to be mined, one of the user in the candidate miner set will be randomly chosen to do the job, and the chosen miner will be removed from the candidate miner set once the job is done. Once candidate miner set is empty, new round of voting will start.

DPoS can produce high throughput without compromising decentrality of blockchain system if everyone is honest and the voting is random. However, it can not be directly applied in our contact tracing framework. In order to motivate people to share their contact information, reward must be given to those who generate contact transactions honestly. If this reward is pecuniary, namely the stack, then people living or working in human-dense areas will gather stacks quickly. This not only motivates people to go out making contacts, but also their votes will gradually become highly weighted due to high stacks, which makes it easily determine the selection of candidate miners. In other words, the whole blockchain system will be dominated by those people who contact people very often.

In order to solve the issue described above, we propose Reputation-Corrected DPoS (RC-DPoS) mechanism. In RC-DPoS, we assign reputation to each user, which is represented by credit $c$. Users will gain reputation reward instead of stack reward for honestly reporting their contact information, while only gain pecuniary stack reward for working as a miner. Specifically, the RC-DPoS mechanism works as follows:

**Step 1:** When new users first join the contact tracing framework, they will be initialized with a fixed start-up stack $s_0$ and credit $c_0$.

**Step 2:** At each round, if the candidate miner set is empty, the candidate selection phase will start. Each user votes another user they trust and users can not vote themselves. The vote is weighted according to the voter’s stack similar as DPoS. But the total votes received by a user will be corrected by his credit. Formally, let $N$ denotes the total number of users in the system. For user $u_i$, $i \in Z^N$, the total vote score accumulated by $u_i$ is calculated according to Equation (1):

$$ G_i = \frac{RF(u_i) + 1}{2} \sum_{u_k} \sum_{s_j} \frac{s_k}{s_j} $$

where the sum is taken over user $u_k$ who votes $u_i$, $s_k$ is the current stack amount of $u_k$, and $c_i$ is the current credit amount of $u_i$. $RF(u_i)$ is the reputation correction factor of user $u_i$, defined as:

$$ RF(u_i) = \frac{c_i - \min_{j \in Z^N}(c_j)}{\max_{j \in Z^N}(c_j) - \min_{j \in Z^N}(c_j)} $$

$RF(u_i) \in [0, 1]$, and $RF(u_i) + 1/2 \in [0.5, 1]$. The intuition behind this equation is we always want users with good reputation to have higher chance to be a candidate miner in order to improve the system security, and meanwhile we also avoid too much punishment applied on other users with lower reputation (maximum 50% off on received votes).

**Step 3:** Rank all users in descending order according to their vote scores. The top $\lceil N/5 \rceil$ users are selected into candidate miners set.

**Step 4:** Every given frequency (3 minutes, 5 minutes or so on) one arbitrary miner selected from the candidate miner set will package all the transactions in the shared transaction pool into a block and append it into the miner’s local blockchain. Then shared transaction pool is empty and waits for new verified transactions. The structure of the blockchain storage is illustrated in Figure 3.

**Step 5:** The miner then broadcasts this update to all users. Users will update their blockchain and the local transaction pool. The miner will be given stack reward and reputation reward. Reward detail will be elaborated in Section VI. Then the miner will be removed from the candidate miner set.

**Step 6:** When a miner fails to do this job within a excusable delay (e.g. 10 minutes) due to network disconnection or system failure, a penalty will be applied on the miner by taking away some credits and no stack reward will be given. Meanwhile, the miner will be removed from the candidate miner list and another miner will be delegated to do the job.

**Step 7:** If the candidate miner set is empty, repeat Step 2.

### VI. Incentive Mechanism

Since the contact tracing framework is highly automatic without a central server, and relies on people to generate transactions and store contact information into blocks, it is crucial to design an incentive mechanism to motivate people to report their contact information honestly. It is also important to ensure the incentive mechanism does not benefit a special group of people. Otherwise, it will make the system centralized and dominated. If the rewards are taking over by a small specific group of people, others will not be willing to share contact information anymore, and the whole system will be barely helpful for contact tracing. In this article, we design the incentive mechanism as a composition of following 4 rewarding policies.

1) Users will be rewarded with $\lceil t \lceil$ credit for generating transactions. The users can not get the reward until the transaction is accepted by the shared transaction pool. This will motivate users to honestly report their contact list. With more credits, according to Equation (1) users will be more likely to be selected as candidate miner and thus can get more credit reward as well as pecuniary stack reward.

2) Users will be rewarded with 1 credit after successfully verifying related pairs in contact transactions. This will motivate users to participate in generating transactions and improve the speed of producing valid transaction.

3) Users will be rewarded with $R_1$ pecuniary reward and 1 credit reward for mining a block. $R_1$ is corresponding to the total amount of transactions that $u_i$ generated.  

$$ R_1 = w * \frac{TF(u_i) + 1}{2}, 
$$

$$ TF(u_i) = 1 - \frac{t_i - \min_{j \in Z^N}(t_j)}{\max_{j \in Z^N}(t_j) - \min_{j \in Z^N}(t_j)}, 
$$

where $w$ is a predefined reward amount (e.g. 5) and $t_i$ is the total number of transaction generated by $u_i$.
$TF(u_i) \in [0, 1]$ is called the transaction correction factor. From the above definition, we could find that the more transaction a user has generated, the lower stack reward will be given to the him. The intuition behind $R_i$ is that we do encourage people to avoid contact in pandemic. Therefore, users who generate more transactions will get lower stack reward $R_i$ each time. In addition, since users who generate many transaction will have higher credit, and they will have higher chance to be a miner. Therefore $R_i$ can balance the pecuniary stack reward among different types of users.

4) Users will be punished if the user fails to do miner’s job. 5 credits will be deducted on the miner for this punishment.

The pecuniary stack reward can be distributed by government or healthcare authorities. Since this system does not require frequent maintenance, the budget can be saved for pecuniary stack reward. Then the contact tracing system will save more money for government by helping control the virus spread.

**VII. SIMULATION**

**A. Simulation Method**

Though there are some well-known real-word trajectory datasets ([36], [37], [38], [39], [40], [41]), they are mostly based on the record obtained from mobile vehicles or cell phone calls, resulting in that the trajectories are not continuous or the number of trajectories are not sufficient in terms of frequency and amount to support the simulation. Since it is hard to collect real-word trajectory in a wide range due to privacy concerns, we simulate on synthetic datasets that simulates different groups of people in real world to demonstrate the effectiveness of the proposed contact tracing framework.

To test our blockchain based contact tracing framework, people in three contact scenarios are considered, where each scenario is decided according to the people density in an area: **Low density (Sparse)**, **Medium density (Medium)**, **High density (Crowded)**. Each scenario can intuitively represent for one kind of real-world human contacting situations. “Sparse” can represent for the people contacting cases in rural area or residential area. “Medium” can represent for the cases in schools, parks or other common public areas. “Crowded” represents for contacting cases happening in some very crowded places, such as shopping malls and sports events.

To simulate the above 3 scenarios, we only need to adjust the frequency of generating transactions, and the length of contact list, witness list. Users are also needs to be created for different contact cases to test if the framework will benefit one kind of users more than another kinds. To achieve this goal, we specify the setting for the three scenarios as follows:

**Low density (Sparse)** case: In each transaction, the length of contact list and witness list conform to the normal distribution $N(\mu = 0, \delta = 2)$ and $N(\mu = 0, \delta = 1)$, respectively. The frequency of generating transaction is 1 cases/hr.

**Medium density (Medium)** case: In each transaction, the length of contact list and witness list conform to the normal distribution $N(\mu = 2, \delta = 4)$ and $N(\mu = 2, \delta = 2)$, respectively. The frequency of generating transaction is 3 cases/hr.

**High density (Crowded)** case: In each transaction, the length of contact list and witness list conform to the normal distribution $N(\mu = 5, \delta = 2)$ and $N(\mu = 7, \delta = 2)$, respectively. The frequency of generating transaction is 12 cases/hr.

We implement the blockchain function with Python 3.7, and all simulations are tested on a machine with Intel Core i7-8750h 8 cores and 32GB memories. Each user is implemented as a thread of python, and all threads are run simultaneously to
simulate real time contact. We randomly generate the contacts for each user without considering reasonable trajectories for them, since the trajectories does not affect the evaluation of the effectiveness and efficiency of the whole framework.

B. Decentraility Evaluation

It is crucial to ensure each user has roughly the same chance to earn stack rewards, and the framework does not skew to a particular people. In other words, the decentrality can be maintained so that every user can be equally motivated to keep contributing to the whole blockchain based system.

We simulate 200 users for each contact scenario, and hence 600 users are put in the whole environment. To measure the decentrality of the system, we draw Lorenz curve, and calculate the Gini coefficient of three factors for all users: user balance (cumulative stack reward), user credits (cumulative reputation reward) and the total number of mined blocks.

Lorenz curve is originally proposed for drawing the cumulative income from different units when they are in the ascending order (42). The closer the income distribution to uniform distribution is, the closer the corresponding Lorenz curve to line $y = x$ is. We extend Lorenz curve in this article to illustrate the decentrality of the proposed RC-DPoS.

The Gini coefficient $gini$ is a measure of inequality of a distribution, which can derived from Lorenz curve (43). It is defined as a ratio with values between 0 and 1. Specifically, the numerator is the area between the Lorenz curve of the distribution and the uniform distribution line; the denominator is the area under the uniform distribution line. Hence, $gini = 0$ indicates perfect equality of a distribution, and $gini = 1$ indicates the distribution is total skew to one sample.

We adopt the DPoS mechanism as the baseline. In the baseline, no credit reward is given to users, and users will get 1 stack reward for generating or verifying transactions. Other settings are same as in the proposed framework. The initial stack credit of users are set to 100. Random voting strategy is adopted when voting for the candidate miners.

Figure 4 shows the results of Gini coefficient and Lorenz curve of the three factors. Since the baseline DPoS mechanism does not consider any credit reward, therefore the Gini coefficient of credit is 0. Figure 4b) shows the Gini coefficient of balance of baseline DPoS remains as high as 0.56, indicating the stack rewards are mostly given to those in dense scenario. The Gini coefficient of mined blocks count is close to 0, because under the random vote strategy, everyone has the same expectation to be selected as a miner. Figure 4c) and (d) shows the results of our proposed framework. As expected, the Gini coefficient of credit is 0.57 when blockchain height is 10k, showing users in dense area can indeed earn credit more than other users. The Gini coefficient of mined blocks count is 0.27 which is higher than 0.12 in baseline, indicating people in dense areas indeed have higher chance to be a miner. Further, the Gini coefficient of credit is 0.19 which is significantly lower than 0.56 in baseline, and demonstrates our RC-PoS and proposed incentive mechanism can successfully balance the stack reward among different groups of users.

C. Robustness Evaluation

Mobile devices are usually with low computational power and low security level, and sometimes may suffer from system failure or network delay and disconnection. All those factors can cause failure of detecting contact case, verifying contact list or receiving transactions. We propose witness for every contact case in our Blockchain Based Contact Tracing Framework, which can improve the robustness of recording correct contact information. A contact transaction $T_{con}$ is verified if all the pairs in $C$ or $W$ are verified. Therefore, even when $C$ is not fully verified, as long as $W$ is verified, which means we have witness contact case $C$, $C$ will be considered valid and be further stored with $T_{con}$ in blocks.

To evaluate the robustness of recording contact information of the proposed system, we set a failure rate $p$ of each user, representing that each user has a probability $p$ of failing to verify the corresponding transaction. Then we compute how many contact cases, that $u_i$ contacts with $u_j$ at timestamp $t$, e.g. $(u_i, u_j, t)$, will be lost comparing with the truth. We use a baseline that there is no witness role in the system, and therefore $(u_i, u_j, t)$ will be lost when both $u_i$ and $u_j$ fails to verify the corresponding tuples in $C$. This is also a common design in exiting works (44,45). We simulate this case for 10 times, and report the average results.

Table 1 shows the simulation results of our 600 users environment mentioned above. It can be seen that our framework can still correctly record nearly 97.12% (1-2.88%) total contact cases even every node has 0.6 probability of failure, while the baseline can only preserve 61.03% contact cases.

D. Attack Resistance

Users may report false or fake contact information to generate more transactions, which may earn more credit reward or pecuniary stack reward. The only way to achieve this attack is through group cheating that several malicious users together create and verify transactions. More specifically, malicious users have two attack approaches to get a fake transaction verified. They can create a contact list where all the contact are malicious users, or put malicious witness in the witness list so that the whole transaction will be verified as long as they create and verify transactions. More specifically, malicious users may report false or fake contact information to generate more transactions, which may earn more credit reward or pecuniary stack reward. The only way to achieve this attack is through group cheating that several malicious users together create and verify transactions. More specifically, malicious users have two attack approaches to get a fake transaction verified. They can create a contact list where all the contact are malicious users, or put malicious witness in the witness list so that the whole transaction will be verified as long as they create and verify transactions. More specifically, malicious users may report false or fake contact information to generate more transactions, which may earn more credit reward or pecuniary stack reward. The only way to achieve this attack is through group cheating that several malicious users together create and verify transactions. More specifically, malicious users have two attack approaches to get a fake transaction verified. They can create a contact list where all the contact are malicious users, or put malicious witness in the witness list so that the whole transaction will be verified as long as
TABLE I: Average Contact Case Loss Percentage at Different $p$

| user failure rate | 0.00%  | 0.13%  | 0.22%  | 0.44%  | 0.91%  | 1.68%  | 2.88%  |
|-------------------|--------|--------|--------|--------|--------|--------|--------|
| our framework     | 0.00%  | 0.16%  | 0.13%  | 0.22%  | 0.44%  | 0.91%  | 1.68%  |
| Baseline          | 0.00%  | 2.16%  | 6.13%  | 11.69% | 19.32% | 27.47% | 38.97% |

In this article, we propose a Blockchain based Contact Tracing Framework, which is a purely decentralized framework without any third-party servers deployed in Bluetooth-enabled mobile devices. We propose the role “witness” in the framework to promote contact tracing data integrity, and the RSA based Transaction Verification Algorithm (RSA-TVA) to verify the correctness of the reported contact information. Reputation Corrected Delegated Proof of Stack (RC-DPoS) consensus mechanism is applied to select miners based on both users’ reputation and users’ stack. An incentive mechanism is further developed to motivate people to keep reporting contact cases honestly and work with RC-DPoS achieving balanced stack reward distribution. In the simulation, we propose the contact tracing environment, which mixes three contact scenarios, namely low people density, medium people density and high people density. The simulation results demonstrate our proposed framework can achieve significantly better reward distribution than the baseline framework, and RSA-TVA incorporated with “witness” role in the framework can hugely improve the system robustness in terms of contact cases loss when mobile devices suffer network disconnection and system failure.

For future work, we will deeply investigate better blockchain storage methods. Since each user needs to store the whole copy of the blockchain, the storage cost will become unacceptable for mobile devices when the user number is large. Though it is believed contact history of 14 days is enough for detecting potential infected cases, recording 14-days contact information may still be a challenge for mobile devices when contact cases are tremendous. Therefore a better blockchain storage method is highly demanded for making more scalable contact tracing applications.
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