LPTD: Achieving Lightweight and Privacy-Preserving Truth Discovery in CIoT

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Abstract

In recent years, cognitive Internet of Things (CIoT) has received considerable attention because it can extract valuable information from various Internet of Things (IoT) devices. In CIoT, truth discovery plays an important role in identifying truthful values from large scale data to help CIoT provide deeper insights and value from collected information. However, the privacy concerns of IoT devices pose a major challenge in designing truth discovery approaches. Although existing schemes of truth discovery can be executed with strong privacy guarantees, they are not efficient or cannot be applied in real-life CIoT applications. This article proposes a novel framework for lightweight and privacy-preserving truth discovery called LPTD-I, which is implemented by incorporating fog and cloud platforms, and adopting the homomorphic Paillier encryption and one-way hash chain techniques. This scheme not only protects devices’ privacy, but also achieves high efficiency. Moreover, we introduce a fault tolerant (LPTD-II) framework which can effectively overcome malfunctioning CIoT devices. Detailed security analysis indicates the proposed schemes are secure under a comprehensively designed threat model. Experimental simulations are also carried out.

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out to demonstrate the efficiency of the proposed schemes.

Keywords: CIoT; truth discovery; lightweight, privacy-preserving.

1. Introduction

Cognitive Internet of Things (CIoT) is a specialized IoT model which capitalizes on the increasing capabilities of mobile devices (with built-in comprehensive sensor sets), which uses cognitive computing techniques to find valuable information from large scale sensing data [1, 2, 3]. By analyzing the big data created by various IoT devices, CIoT is able to provide deeper insights, high-level intelligence, and further create values for people.

Despite the proliferation of CIoT, there are some increasing concerns which may impede its wide adoption. For example, the sensory data captured and provided by different devices is usually not directly usable or reliable, as it may be distorted due to reasons such as, lack of sensor calibration, poor sensor quality, background noise, and even the intent to deceive. Therefore, an important task of the CIoT applications is to discover truthful information from the sensory data. This task, called truth discovery, has drawn significant attention [4, 5, 6]. Typically, the common principle to execute truth discovery is weighted aggregation that assigns a higher weight to a particular device if data reported by it is closer to the aggregated results from all devices. Moreover, a device’s data is given higher value if the device has higher weight due to its past performance [7, 8]. By performing truth discovery, accurate sensory data can be obtained, and such data will greatly promote the effectiveness of CIoT applications.

Although having significantly improved data accuracy, the challenge for truth discovery, is that the sensory data is highly sensitive and should be well protected, especially considering that sensory data may contain personal information [9, 10, 11]. For example, geo-tagging services can publish timely and accurate localization of specific objects (e.g., pothole, automated external defibrillator, litter, etc.). However, this may lead to exposure of participating users’ sensitive geo-location and/or movement patterns. Aggregated health statistics
(i.e., treatment outcomes) may provide valuable information regarding medical devices’ effects or new drugs, but may threaten the privacy of participating patients. Meanwhile, user reliability (i.e., weight) is another private information which should be well protected. From user reliability information, the attacker may infer details of participating users’ education, skills, and personality traits. For example, aggregating opinions regarding challenging social problems may lead to a better solution. However, the leakage of reliability may disclose users’ education and intellectual level.

Several studies have tried to preserve users’ privacy in the applications of truth discovery [7, 8, 12]. However, most of them are not efficient or cannot be applied in real-life CIoT applications. For example, Du et al. [13] tried to find a reliable key management scheme, Miao et al. [7] proposed a cloud-based privacy-preserving truth discovery scheme to protect users’ sensory data. However, by using threshold Paillier cryptosystem [14], their scheme is not efficient. To improve efficiency, Xu et al. [8] proposed a lightweight and privacy-preserving discovery scheme by using the additive homomorphic privacy-preserving techniques. Miao et al. [12] further designed a lightweight truth discovery framework by using two non-colluding cloud platforms. Although their schemes achieve better efficiency, they cannot be applied in CIoT applications, especially in scenarios where some IoT devices may not deliver their data timely [15]. Moreover, all the above schemes cannot defend from external attackers who inject false data into the system. Hence, there is a need for an efficient truth discovery scheme, which not only protects users’ privacy, but is also able to mitigate false data injection attacks and give fault tolerance.

In this paper, to address these challenges, we present a lightweight privacy-preserving truth discovery scheme in CIoT, called LPTD-I, to protect devices’ privacy (i.e., sensory data and reliability information), and resist false data injection attacks. The framework is implemented by involving fog and cloud platforms, adopting homomorphic Paillier encryption, and one-way hash chain techniques. In this framework, the fog node authenticates the data submitted from devices and aggregates the data before delivering it to the cloud. In
addition, we exploit the properties of modular arithmetic to design a data aggregation algorithm which is efficient and privacy preserving.

Although LPTD-I can defend against the false data injection attack launched by external attackers, it is not fault-tolerant. Thus, we exploit the modified Paillier cryptosystem and propose a framework (LPTD-II) suitable for the scenarios where some IoT devices may stop delivering data due to device failure, to the fog node. In this framework, the secret key is split into two parts, and the fog devices can cooperate with the cloud to recover the aggregated results successfully.

In summary, the contributions of this paper are:

- We propose a novel lightweight and privacy-preserving truth discovery scheme in CIOT, called LPTD-I. This scheme not only preserves the privacy of users (i.e., sensory data and reliability information), but also achieves high efficiency.

- For the scenarios where some IoT devices stop reporting sensory data to the fog node, an upgraded technique called LPTD-II, is proposed to achieve fault tolerance.

- Detailed security analysis indicates the proposed schemes are secure under an elaborate threat model. Additionally, experimentation shows the efficiency of both the proposed schemes.

The rest of this paper is organized as follows. In section 2, we give the problem definition which includes the system model, security model, and design goals. In section 3, we describe some preliminary. The details of the proposed LPTD schemes are described in section 4, followed by the security analysis and performance analysis in section 5 and section 6, respectively. In section 7, we discuss the related work. Finally, we draw the conclusion in the last section.
2. Problem Definition

The system model, security model, and design goals are outlined in the following sections.

2.1. System Model

The system model shown in Fig. 1 is comprised of four entities: IoT devices, the fog node, the cloud, and a trusted authority.

- **IoT devices**: Each IoT device is equipped with sensing, communication, and computing capabilities, which can enable the device to collect sensory data, report data, and perform simple computation operations. Note that, since most IoT devices are resource-constrained, the computational costs for operations performed at these devices should be minimal.

- **Fog node**: The fog node acts as a middle layer between the IoT devices and the cloud, and is deployed at the edge of network. They can process/deliver data for the devices and/or cloud. In our schemes, it also aggregates all reports from IoT devices, and forwards resulting data to the cloud.

- **Cloud**: It receives all data from the IoT devices through the fog node. For each object, it generates an initial ground truth, and iteratively updates the truth in cooperation with the fog node.

- **Trusted authority (TA)**: TA is a trusted third party, and it bootstraps the whole system. It generates keys and assigns them to all entities. Once the system is up and running, the TA remains offline.

We formalize the truth discovery approach as follows: Suppose there are $K$ IoT devices and $M$ objects, we use $x^k_m$ to denote the observed value of device $k$ for object $m$. For all devices, $\{w_1, w_2, \cdots, w_K\}$ are used to denote their reliabilities (i.e., weights). Each object is assigned an initial ground truth. The goal of the proposed scheme is to calculate the ground truths $\{x_m^*\}_{m=1}^M$ for all
objects while protecting the observed value and weight of each device from being disclosed to others. Table 1 summarizes the main notations used in this work.

| Symbol | Definition |
|--------|------------|
| $K$    | Number of devices |
| $k$    | Index of devices, $k \in \{1, K\}$ |
| $w_k$  | Weight of device $k$ |
| $M$    | Number of objects |
| $m$    | Index of objects, $m \in \{1, M\}$ |
| $x^k_m$ | Observed value of device $k$ for object $m$ |
| $x^*_m$ | Truth for the object $m$ |
| $std_m$ | The standard deviation for the $m$-th object |

2.2. Security Model

- TA is considered to be fully trusted, and it cannot be breached by any attacker.

- The fog and cloud elements are honest-but-curious. This means that they...
will follow the protocol, but are also curious regarding device/user details. Note that, in our threat model, they do not collude with each other.

- The honest-but-curious IoT devices will follow the protocols. They can collude with other entities (i.e., other IoT devices, the fog, and the cloud), but we emphasize that they cannot collude with the fog and the cloud simultaneously.

- Since the focus of this work is to design a privacy-preserving truth discovery approach, internal attacks are not considered, i.e., all entities cannot be compromised at the same time. However, we do allow that some IoT devices may malfunction or stop reporting data intermittently. Moreover, external attackers may also launch false data injection attacks. Hence, the fog node should filter such data before transmitting them to the cloud.

2.3. Design Goals

The goal of the proposed scheme is to design an efficient and privacy-preserving truth discovery approach which can protect devices’ privacy and reduce computational costs. Security issues as studied in [16, 17, 18] should be solved in our work. In order to achieve this, following design goals must be guaranteed:

- Privacy: The proposed scheme should preserve the privacy. The fog node and cloud can obtain the truthful values, but they cannot obtain individual IoT devices’ information (i.e., sensory data and reliability information).

- Security: The scheme should be resistant to false data injection attacks launched by external attackers. In other words, the fog node should authenticate the IoT devices and filter the false data before transmitting it to the cloud.

- Fault Tolerance: In case where some IoT devices malfunction and stop reporting data, the cloud should still be able to obtain acceptable levels of aggregated data.
• Efficiency: The computational cost at each system element should be as little as possible.

3. Preliminaries

In order to better explain the proposed schemes, we first introduce the general process of truth discovery and cryptographic tools, in the following parts.

3.1. Truth Discovery

Truth discovery in large scale sensory data has been widely studied in the past. Although the algorithmic details of different solutions are a bit different from each other, the fundamental principle of assigning device weights and estimating ground truth is same. At the initialization point of truth discovery algorithm, random ground truths are assigned, which are iteratively updated until convergence is achieved. Algorithm 1 shows the general truth discovery process.

**Weight Update:** In this step, the ground truth of each object is assumed to be fixed. Typically, a device is assigned higher weight if it provides data, which is closer to the ground truth, and vice versa. Inspired by the works of CRH [4] (as it gives good practical performance), we calculate weight as follows:

\[
wk = \log \left( \frac{\sum_{k=1}^{K} \sum_{m=1}^{M} d(x^k_m, x^*_m)}{\sum_{m=1}^{M} d(x^k_m, x^*_m)} \right) \tag{1}
\]

where \(d(\cdot)\) is a distance function utilized to measure the difference between the ground truth and observation by devices. Moreover, \(d(\cdot)\) is dependent on application use case. The two most common type of data (i.e. continuous and categorical) are considered in this work.

In applications, such as environmental monitoring, sensory data (e.g., temperature, humidity, etc.) is continuous in nature. Hence the following distance function is adopted:

\[
d(x^k_m, x^*_m) = \frac{(x^k_m - x^*_m)^2}{\text{std}_m} \tag{2}
\]
where $\text{std}_m$ is used to represent the standard deviation of all the users’ observations for object $m$.

Other use cases like public opinion polls have collected data that is categorical in nature, that is based on the selection of choices. In these applications, only one is correct among the multiple candidate choices. Thus, an observation vector $x_m^k = (0, \ldots, 1, \ldots, 0)^T$ is defined to denote that the $k$-th device selects the $q$-th candidate choice for object $m$. The following function is used to measure the distance between the observation vector and the ground truth vector:

$$d(x_m^k, x_m^*) = (x_m^k - x_m^*)^T (x_m^k - x_m^*) \quad (3)$$

**Truth Update:** In this step, weights are assumed to be fixed. We calculate the ground truth for $m$-th object as follows:

$$x_m^* \leftarrow \frac{\sum_{k=1}^{K} w_k \cdot x_m^k}{\sum_{k=1}^{K} w_k} \quad (4)$$

$x_m^*$ is considered ground truth, if data is continuous. Contrary to this, $x_m^*$ is considered a probability vector where each element represents the probability of a choice being true, if the data is categorical. In this case, the final ground truth is the choice with highest probability.

3.2. Cryptographic Tools

In order to perform encryption, we make use of the following algorithms.

3.2.1. Modified Paillier cryptosystem

A modified Paillier cryptosystem to encrypt devices’ sensitive information \cite{19} is used to realize privacy-preserving truth discovery. This modified Paillier cryptosystem consists of the following four components:

- **Key Generation:** Given a security parameter $\kappa$, two large safe prime numbers $p$, and $q$ are calculated as $p = 2p' + 1$ and $q = 2q' + 1$, where $|p| = |q| = \kappa$, $p'$ and $q'$ are also two large primes. Then, Compute $n = pq$, 


Algorithm 1: Truth Discovery Algorithm

Input: Observations from $K$ devices: $\{x^k_{m,k}\}_{m,k=1}^{M,K}$

Output: Ground truths for $M$ objects: $\{x^*_m\}_{m=1}^{M}$

1. Randomly initialize the ground truth $x^*_m$;
2. for iteration $= 1, 2, \ldots, \text{iteration}_{\text{max}}$ do
   3. for $k = 1, 2, \ldots, K$ do
      4. Update device weight (see Eq. (1));
   5. for $m = 1, 2, \ldots, M$ do
      6. Update ground truth (see, Eq. (4))
3. return $\{x^*_m\}_{m=1}^{M};$

and $\lambda = \text{lcm}(p - 1, q - 1) = 2p'q'$. Choose a random value $\mu \in \mathbb{Z}_{n^2}$, and a random number $x \in [1, \lambda(n^2)/2]$. Finally, the public key is set as $pk = (n, g = \mu^2 \mod n^2, h = g^x)$, and the secret key is $x$.

- **Encryption:** Suppose there is a message $m \in \mathbb{Z}_n$ to be encrypted. Select a random value $r \in \mathbb{Z}_{n^2}$, and calculate the ciphertexts ($c_1, c_2$) as $c_1 = g^r \mod n^2$ and $c_2 = h^r(1 + n \cdot m) \mod n^2$.

- **Decryption:** Given ($c_1, c_2$), the message $m$ can be decrypted by computing $m = c_2(c_1)^{x-1} \mod n^2$.

- **Proxy Re-encryption:** Split the secret key $x$ into two random shares $x_1, x_2$, such that $x = x_1 + x_2$. Then, the ciphertexts ($c_1, c_2$) can be partially decrypted as $(\tilde{c}_1, \tilde{c}_2)$ by using $x_1$, where $\tilde{c}_1 = c_1$, and $\tilde{c}_2 = c_2/(c_1)^x \mod n^2$. Lastly, $(\tilde{c}_1, \tilde{c}_2)$ can be decrypted using $x_2$ to recover $m$.

3.2.2. One-way hash chain

As a common cryptographic tool, various applications [20] have used one-way hash chain. In this work, we use this technique to authenticate the IoT devices. Suppose there is a secure hash function: $h : \{0, 1\}^* \rightarrow h : \{0, 1\}^l$, a one-way hash chain can be defined as a set of values $(m_0, m_1, \ldots, m_n)$, where
is randomly chosen, and \( m_i = h(m_{i+1}) \) for \( i = 0 \) to \( n - 1 \). Note that, it is easy to compute \( m_x \), where \( x < y \), but becomes computationally infeasible for \( m_z \), if \( y < z \). Fig. 2 depicts the structure of one-way hash chain.

![One-way hash chain structure](image)

Figure 2: One-way hash chain structure.

### 3.2.3. Properties under modulo \( n^2 \)

In modified Paillier cryptosystem, for any message \( m_i \in \mathbb{Z}_n, i = 1, 2, \cdots, n \), the following equation holds

\[
\prod_{i=1}^{n} (1 + n \cdot m_i) \equiv (1 + n \sum_{i=1}^{n} m_i) \mod n^2.
\]  

(5)

This property can be easily proven by using mathematical induction, which can be found in [15].

### 4. Proposed LPTD Schemes

In this section, we give the details of the proposed two LPTD schemes in CIoT, which mainly include the following parts: system initialization, design overview, LPTD-I scheme, and LPTD-II scheme.

#### 4.1. System Initialization

TA is considered to be fully trusted, and it bootstraps the whole system. Given a security parameter \( \kappa \), TA selects two large safe prime numbers \( p, q \), where \(|p| = |q| = \kappa\). Following this, it then generates the public key \( pk \) & private key \( sk \) of the modified Paillier cryptosystem as \( pk = (n, g, h) \), \( sk = x \), where \( n = p \cdot q \), and \( h = g^x \mod n^2 \). Then, TA randomly splits \( sk \) into two shares \( x_1 \) and \( x_2 \), such that \( x = x_1 + x_2 \). Suppose there are \( K \) IoT devices in the network, TA generates \( K + 2 \) vectors \([s_0, s_1, \cdots, s_{K+1}]\), each contains \( w \) random numbers, such that,
\[
\sum_{k=0}^{K+1} s_{kj} \equiv 0 \mod n^2
\]

where \(j \in [1, w]\).

TA selects a secure cryptographic hash function \(h\), where \(\{0, 1\}^* \rightarrow \{0, 1\}^l\).

Since the truth and weight are iteratively updated, we divide the number of iterations into \(w\) times, and at every iteration, each device will report its observation or weighted data. TA generates \(K\) one-way hash chains \(HC_1, HC_2, \ldots, HC_K\), where \(HC_k = (h_{k0}, h_{k1}, \ldots, h_{kw})\), \(h_{k0} \in \{0, 1\}^*\), and \(h_{kj} = h(h_{k(j+1)}||j)\), \(1 \leq k \leq K\), \(0 \leq j \leq w - 1\).

Once these values are configured, TA assigns the keys to devices, fog node, and cloud elements, as given below:

- For the device \(k\), TA computes \(S_k = \{(g^{s_k1}, h^{s_k1}), (g^{s_k2}, h^{s_k2}), \ldots, (g^{s_kw}, h^{s_kw})\}\) and assigns \(S_k\), the hash chain \(HC_k = \{h_{k0}, h_{k1}, \ldots, h_{kw}\}\), and the public key \(pk\).

- For the fog, TA assigns a share of the private key \(x_1\), the hash chain heads of \(K\) devices \((h_{10}, h_{20}, \ldots, h_{K0})\), the secret key vector \(S_{K+1} = \{h^{s(K+1)1}, h^{s(K+1)2}, \ldots, h^{s(K+1)w}\}\), the public key \(pk\), and the shared key \(ss\) to the fog device.

- For the cloud, TA assigns the other share of private key \(x_2\), the secret key vector \(S_0 = \{h^{s01}, h^{s02}, \ldots, h^{s0w}\}\), together with the public key \(pk\), and the same shared key \(ss\).

### 4.2. LPTD Scheme: General Overview

Once the devices obtain the observed values, LPTD will carry out the following two phases:

- **Phase 1: Secure weight update.** First, every IoT device encrypts the observed value by using the cryptographic tool. Then, these ciphertexts are submitted to the fog node for aggregation and the aggregated value is further submitted to the cloud to calculate the standard deviation of
the observed values, which will be then sent to every device. After that, every device computes the distances between the observed values and the ground truths. Finally, the fog and the cloud cooperatively and iteratively update the weights.

- **Phase 2: Secure truth update.** When each device receives the aggregated differences from the fog device, they first calculate the weight, the weighted observed values, and then send them to the fog device in ciphertexts. Lastly, the fog and the cloud will calculate the ground truth $x_m^*$. 

During the procedure of LPTD, all operations are executed in ciphertexts. Hence, an entity only knows its own information, and the devices’ sensitive information (i.e., observed value and weights) is not leaked to other entities.

4.3. LPTD-I Mechanism

In this subsection, we first describe the details of LPTD-I, which is able to protect the devices’ privacy and resist external false data injection attacks.

It is important to note that the sensory data from IoT devices may not be integers, but the cryptosystem used in this scheme is defined for integer values. Thus, to deal with this problem, a parameter $T$, of magnitude 10, is utilized to round off the observed values. As an example, device $k$ gets the observed value $x_{km}^*$ for the object $m$. We can use $T$ to multiply $x_{km}^*$ as $\lfloor x_{km}^* \cdot T \rfloor$, and the final result can be recovered by dividing $T$. For easy understanding in this work, all observed values and intermediate results are assumed to be preprocessed as above.

4.3.1. Secure weight update

**Step W1.** The cloud delivers the estimated ground truth $x_m^*$ for object $m$ to all devices. If it is the first iteration, the estimated ground truth is randomly initialized. Otherwise, it will be obtained from the previous iteration.

**Step W2.** When the device $k$ obtains $x_m^*$, it first computes the difference between $x_{km}^*$ and $x_m^*$ according to Eq. 2 and then aggregates the differences of
$M$ objects as $\text{Dist}_k = \sum_{m=1}^{M} d(x^k_m, \ast_m)$. Before submitting $\text{Dist}_k$ to the fog node, the device uses its secret key $S_{kj}$ to compute

$$C_{kj} = (1 + n \cdot \text{Dist}_k) \cdot h^{s_kj} \text{ mod } n^2,$$

and then uses the hash value $h_{kj}$ to compute

$$\text{mac}_{kj} = h(C_{kj} \parallel h_{kj}),$$

where $j$ denotes the iteration number. After that, the device submits $(C_{kj}, h_{kj}, \text{mac}_{kj})$ to the fog. The operation may not seem time efficient, but they can be efficiently executed, as $h^{s_kj}$ has been calculated by TA in advance.

**Step W3.** After receiving $(C_{kj}, h_{kj}, \text{mac}_{kj})$ in the $j$-th iteration, the fog node checks the validity of the IoT device, and aggregates the reports as follows:

- Check hash chain node $h_{kj}$: Assume that the fog has authenticated $h_{k(j-1)}$ in the previous $(j-1)$-th iteration, it can easily verify $h_{kj}$ according to $h_{k(j-1)} \overset{?}= (h_{kj} \parallel j)$. If it holds, $h_{kj}$ is accepted. Otherwise, it is rejected.

- Check $\text{mac}_{kj}$: If $h_{kj}$ is valid, the fog node further verifies $\text{mac}_{kj}$ by computing

$$\text{mac}'_{kj} = h(C_{kj} \parallel h_{kj}),$$

and checking if $\text{mac}'_{kj} \overset{?}= \text{mac}_{kj}$. If it holds, $\text{mac}_{kj}$ is accepted. Otherwise, it is rejected.

- Data aggregation: After receiving $(C_{1j}, C_{2j}, \ldots, C_{Kj})$ from all devices, the fog node utilizes its secret key $S_{(K+1)j}$ to obtain the aggregated result as

$$C_j = \prod_{k=1}^{K} (C_{kj}) \cdot h^{s_{(K+1)j}} \text{ mod } n^2,$$

and then use the shared secret key $ss$ to compute

$$\text{mac}_j = h(C_j \parallel j \parallel ss).$$

Following this, the fog device delivers $(C_j, \text{mac}_j)$ to the cloud.
\textbf{Step W4.} Upon receiving \((C_j, mac_j)\) in the \(j\)-th iteration, the cloud first checks data validity according to \(mac_j = h(C_j || j || ss)\). If it holds, the cloud executes the following operations to obtain the aggregated result \(s\).

- The cloud utilizes its secret key \(S_{0j}\) to compute

\[
C'_j = C_j \cdot h^{s_{0j}} \mod n^2
\]

\[
= (\prod_{k=1}^{K} C_{kj}) \cdot h^{s_{0j} + s_{(K+1)j}} \mod n^2
\]

\[
= (\prod_{k=1}^{K} (1 + n \cdot Dist_k) \cdot h^{s_{kj}}) \times h^{s_{0j} + s_{(K+1)j}} \mod n^2
\]

\[
= \prod_{k=1}^{K} (1 + n \cdot Dist_k) \cdot \prod_{k=0}^{K+1} h^{s_{kj}} \mod n^2
\]

\[
= \prod_{k=1}^{K} (1 + n \cdot Dist_k) \cdot h^{\sum_{k=0}^{K+1} s_{kj} \rightarrow 0} \mod n^2
\]

\[\text{(12)}\]

- The cloud can obtain \(\sum_{k=1}^{K} Dist_k\) by computing

\[
\text{sum}_d = \sum_{k=1}^{K} Dist_k = \frac{C'_j - 1}{n}.
\]

\[\text{(13)}\]

The cloud then selects a random number \(r_{j1} \in Z_{n^2}\) to blind \(\text{sum}_d\) as \(\log(r_{j1} \cdot \text{sum}_d)\) before forwarding it to the fog node.

\textbf{Step W5.} After receiving \(\log(r_{j1} \cdot \text{sum}_d)\), the fog node selects a random number \(r_{j2} \in Z_{n^2}\), and computes

\[
\log(\widehat{\text{sum}}_d) = \log(r_{j1} \cdot \text{sum}_d) + \log(r_{j2})
\]

\[
= \log(r_{j1} r_{j2} \cdot \text{sum}_d).
\]

\[\text{(14)}\]
After that, the fog delivers $\log(\sum_d)$ to the device. The device can calculate its weight as

$$w_k = \log(\sum_d) - \log(Dist_k)$$

$$= \log(r_j r_j \cdot \sum_{k=1}^{K} Dist_k) - \log(Dist_k)$$

$$= \log\left(\frac{r_j r_j \cdot \sum_{k=1}^{K} Dist_k}{Dist_k}\right)$$

$$= r_j \cdot w_k,$$

(15)

where $r_j = r_{j1} \cdot r_{j2}$.

As shown in Eq. 15, the standard deviation $std_m$ is necessary to calculate the difference between the observed value and the ground truth. Thus, it should be computed first. The calculations can be shown as follows:

- The IoT device $k$ encrypts the observed value $x_{km}$ according to Eq. 7 and forwards the ciphertexts to the fog node.
- On reception of ciphertexts, the fog node and the cloud cooperatively calculate $\sum_m = \sum_{k=1}^{K} x_{km}$, and $\overline{x_m} = \sum_m / K$ following the above operations, and then send $\overline{x_m}$ to all devices.
- The device $k$ calculates $d_{km} = (x_{km} - \overline{x_m})^2$, and encrypts $d_{km}$ before uploading it to the fog node.
- Upon receiving all the ciphertexts, the fog and the cloud cooperatively calculate $\sum_d = \sum_{k=1}^{K} d_{km}$, and further obtain $std_m = \sqrt{\sum_d / K}$.

At last, $std_m$ is forwarded to all devices.

4.3.2. Secure truth update

Upon updating the weights, it is time to update the ground truth. The details are shown as follows.

**Step T1.** The device $k$ calculates the weighted data as $r_j \cdot x_{km} \cdot w_k$, and then encrypts the weighted data and weight as

$$\begin{align*}
W_{kj,1} &= (1 + n \cdot (r_j \cdot x_{km} \cdot w_k)) \cdot h^{s_k} \mod n^2 \\
W_{kj,2} &= (1 + n \cdot (r_j \cdot w_k)) \cdot h^{s_k} \mod n^2
\end{align*}$$

(16)
Then, following the same operations in secure weight update, \( k \) generates \( \text{mac}_{kj} = (W_{kj,1}||W_{kj,2}||h_{kj}) \), and uploads \((W_{kj,1}, W_{kj,2}, h_{kj}, \text{mac}_{kj})\) to the fog node.

**Step T2.** After checking the data validity, the fog uses its secret key \( S_{(K+1)j} \) and runs the aggregation operations according to Eq. 10. It then uploads \((W_j, \text{mac}_j)\) to the cloud.

**Step T3.** The cloud uses its secret key \( S_{0j} \), and computes \( r_j \cdot \sum_{k=1}^{K} (x^k \cdot w_k) \) and \( r_j \cdot \text{sum}_{k=1}^{K} w_k \) according to Eq. 12. The cloud then updates the ground truth as

\[
x^*_m = \frac{r_j \cdot \sum_{k=1}^{K} (x^k \cdot w_k)}{r_j \cdot \sum_{k=1}^{K} w_k}.
\]

(17)

Note that, we only consider continuous data in the proposed scheme. Since the difference function between continuous and categorical data is different, the distance between the observed vector \( x^d_k \) and the ground truth vector \( x^*_d \) can be easily computed according to Eq. 3, which can be seen as a special case in the proposed LPTD schemes.

After combining the above two procedures, the privacy-preserving truth discovery algorithm is shown in Algorithm 2.

### 4.4. LPTD-II Mechanism

In real-life CIoT applications, one IoT device \( l \) may not submit its data in time due to malfunctions, low battery, network delay, etc. Thus, the aggregated result is not accurate based on the previous operations, because \( \sum_{k=0}^{K+1} s_k \equiv 0 \mod n^2 \) does not hold. To achieve fault-tolerance, we design another efficient and privacy-preserving truth discovery approach, called LPTD-II. In the following, we only show how to recover the aggregated results from the ciphertexts in the cloud. Other details are omitted, as they are similar to LPTD-I.

When submitting ciphertexts to the fog node, besides \( C_{kj}, W_{k,1}, W_{k,2} \), the device \( k \) needs to submit another ciphertext \( G_{kj} = g^{sk_j} \mod n^2 \). Note that, this ciphertext is also pre-computed by TA, and delivered to the fog node in advance to save computational cost and communication overhead.
After receiving $G_{kj}$ from all devices except the device $j$, the fog node first aggregates them as

$$G_j = \prod_{k=1,k\neq l}^K G_{kj},$$

and then uses its share of the secret key $x_1$ to partially decrypt the aggregated ciphertexts as

$$C_{t,1} = \frac{C_j}{(G_j)^{x_1}} \mod n^2.$$  

The cloud further computes

$$C_{t,2} = \frac{C_{t,1}}{(G_j)^{x_2}} \mod n^2$$

with $x_2$, and obtains the aggregated result $M$ by calculating

$$M = \left(\frac{C_{t,2} - 1}{n}\right) \mod n^2.$$  

5. Security Analysis

The security properties of proposed LPTD schemes are of prime importance. Here, we show how the proposed schemes can achieve privacy preservation and effectively defend against false data injection attacks.

**Defense against false data injection:** To authenticate the validity of data in each iteration, one-way hash chain technique is applied in the LPTD schemes. For each device, if the hash value $h_{k(j-1)}$ is authenticated in the $(j-1)$-th iteration, $h_{kj}$ can be authenticated according to $h_{k(j-1)} = h(h_{kj}||j)$ as it is hard to obtain $h_{kj}$ from $h_{k(j-1)}$ due to the properties of one-way hash function. In fact, only if a device reports its data in the $j$-th iteration, the fog can get a fresh $h_{kj}$. If the $h_{kj}$ is not fresh in the $j$-th iteration, it can be considered as false data by replaying $h_{kj}$. The fog can identify and filter this data. Thus, the proposed LPTD schemes can defend against the false data injection attack.

**Privacy preservation:** In LPTD schemes, the observed value of a device $k$ is encrypted as $C_{kj} = (1 + n \cdot \overline{m}) \cdot h^{x_k}$, if we look at $\text{Dist}_{kj}$ as a message $\overline{m}$. Note that $(1+n \cdot \overline{m}) \cdot h^{x_k}$ is a valid Paillier ciphertext. An external attacker cannot get
Algorithm 2: Privacy-Preserving Truth Discovery Algorithm

**Input:** Observations from $K$ devices: $\{x^k_{m,k}\}_{m,k=1}^{M,K}$

**Output:** Ground truths for $M$ objects: $\{x^*_m\}_{m=1}^M$

1. The cloud randomly initializes the ground truth $\{x^*_m\}_{m=1}^M$.
2. Each device encrypts the observed value $x^k_m$ as $Enc(x^k_m)$ and $Enc(x^k_m)^2$, and sends both to the fog.
3. After receiving all ciphertexts, the fog cooperates with the cloud to calculate the standard deviation $std_m$ for object $m$, and delivers it to all devices.
4. for $iteration = 1, 2, \ldots, iteration_{max}$ do
   5. for $k = 1, 2, \ldots, K$ do
      6. Each device calculates the difference between $x^k_m$ and $x^*_m$, and the sum of differences for $M$ objects $Dist_k$. Then, $Dist_k$ is encrypted as $Enc(Dist_k)$, and submitted to the fog node.
      7. After obtaining $Enc(Dist_k)$, the fog cooperates with the cloud to recover $log(sum_d)$, and further blind $log(sum_d)$ by choosing two random values $r_{j1}$ and $r_{j2}$. Then, $log(\tilde{sum}_d)$ is delivered to all devices.
      8. After obtaining $log(\tilde{sum}_d)$, each device calculates its weight, and weighed data. Both of them will be uploaded to the fog node after encryption.
   9. for $m = 1, 2, \ldots, M$ do
      10. When the fog receives $Enc(x^k_m \cdot w_k)$ and $Enc(w_k)$, it cooperates with the cloud to calculate the ground truth $x^*_m$, and then sends the truth to all devices.
11. return The ground truths $\{x^*_m\}_{m=1}^M$.

The fog node is also curious about $\overline{m}$. However, without knowing the other share of the secret key $x_2$, it will not be able to
recover the sensitive data. For the weight information, $x_m^k \cdot w_k$ and $w_k$ are encrypted as $W_{k,1}$ and $W_{k,2}$ respectively. As $W_{k,1}$ and $W_{k,2}$ are both Paillier ciphertexts, an external attacker cannot recover the weight information. Notice that, the attacker may perform the following operation to calculate the weight,

$$\frac{W_{kj,1}}{W_{kj,2}} = \frac{1 + n \cdot (r_j \cdot x_m^k \cdot w_k)}{1 + n \cdot (r_j \cdot w_k)}.$$  \hspace{1cm} (22)

However, since $x_m^k$, $w_k$, and $r_j$ are unknown, the attacker cannot calculate them from Eq. 22. The attacker may build more equations to recover $x_m^k$ as

$$\begin{align*}
W_{k1,1} &= (1 + n \cdot (r_1 \cdot x_m^k \cdot w_{k1})) \cdot h^x\mod n^2 \\
W_{k1,2} &= (1 + n \cdot (r_1 \cdot w_{k1})) \cdot h^x\mod n^2 \\
W_{k2,1} &= (1 + n \cdot r_2 \cdot x_m^k \cdot w_{k2}) \cdot h^x\mod n^2 \\
W_{k2,2} &= (1 + n \cdot r_2 \cdot w_{k2}) \cdot h^x\mod n^2 \\
&\cdots
\end{align*}$$ \hspace{1cm} (23)

From Eq. 23 we can see that with more equations introduced, more random numbers (i.e., $r_j$) will be introduced. Since $r_j = r_{j1} \cdot r_{j2}$, only if the fog node colludes with the cloud, the attacker can obtain $r_j$. Nevertheless, under our security model, there is no collusion between the fog and the cloud. Hence, the scheme preserves the privacy, and passes the security model.

6. Performance Analysis

In addition to security model evaluation, we also perform experimental evaluation for communication and computational costs of both proposed schemes.

6.1. Communication Overhead

To show the communication overhead of LPTD, we compare the proposed schemes with the PPDP \cite{7}, which encrypts the data by calculating $c = g^{m \cdot r_n}$ mod $n^2$, under the same setting. Here, we assume the bit length of $|n^2|$ is set as $U$. However, we omit the cost of authentication for all schemes as a fairness consideration. During the process of weight update in LPTD-I, each
device needs to submit $Enc(Dist_k)$, which costs $U$ bits. In PPDP, $k$ needs to submit $Enc(Dist_k)$ and $Enc(\log(Dist_k))$, which cost $2U$. In the procedure of truth update, PPDP and LPTD-I need to submit $M \cdot Enc(w_{m}^{w_{k}} \cdot w_{k})$ and $Enc(w_{k})$, which cost $(M + 1)U$, where $M$ is the number of objects. Compared with LPTD-I, LPTD-II needs to submit one more $g^{w_{k}} \mod n^{2}$ to execute the decryption operation. However, in reality, $g^{w_{k}} \mod n^{2}$ can be submitted to the fog in advance to receive communication overhead, as it is constant. Table 2 summarizes the communication overhead of all schemes in each phase for each device.

| Phase of weight update | Phase of truth update |
|------------------------|-----------------------|
| PPDP                   | 2$U$                  | $(M + 1)U$             |
| LPTD-I                 | $U$                   | $(M + 1)U$             |
| LPTD-II                | 2$U$                  | $(M + 2)U$             |

6.2. Computational Costs

We compare the computational costs of LPTD and PPDP schemes by implementing all schemes in Java, and run several experiments on a system with 2.5 GHz Intel Core i7 and 16GB RAM. The number of iteration is set as 10, as average result of 10 experiments are used for comparisons.

As shown in Fig. 3(a), we compare the run time of PPDP with 100 devices and varying number of objects. It can be observed that as the number of objects increases, the run time of LPTD remains far less than that of PPDP. For example, when the number of objects is 800, LPTD-I and LPTD-II cost 8.098s and 8.696s to finish the truth discovery respectively, while PPDP takes 71.172s. This is due to the reason that PPDP needs to perform time-consuming module exponent operations, while only multiplication operations are required in LPTD. The single module multiplication operation can be done in advance, which provides an added benefit. Note that, LPTD-I performs better than
LPTD-II, since LPTD-II needs to execute 2 decryption operations to recover the aggregated results, while LPTD-I only needs to perform 2 multiplication operations.

Similarly, from Fig. 3(b), we can also find that the total running time of LPTD is less than that of PPDP when the number of devices ranges from 100 to 700, while the number of objects is fixed at 100. When the number of devices reaches 700, LPTD-I and LPTD-II take 34.079s and 37.606s to finish the truth discovery respectively, while PPDP needs 136.754s. This also confirms the efficiency of our scheme.

![Figure 3: (a) Total running time with varying number of objects. (b) Total running time with varying number of devices.](image)

Fig. 4 shows the run time of weight update and truth update with varying number of objects. Here, we set the number of devices as 100. As it can be observed from Fig. 4(a), the run time of PPDP and LPTD are relatively stable. The reason is that, although more objects are introduced, each device only needs to perform 2 encryption operations in PPDP, and 1 encryption operation in LPTD (i.e., $(Enc(\text{Dist}_k), Enc(\log \text{Dist}_k))$ vs. $(Enc(\text{Dist}_k))$) in the weight update phase. Since PPDP needs to execute module exponent operations, it costs higher running time than LPTD-I and LPTD-II. In Fig. 4(b), the running time of all schemes grow linearly. The reason is that more truths need to be updated as the number of objects increases. It can be also found that PPDP takes higher time to finish same computations.
Figure 4: (a) Running time of weight update with varying number of objects. (b) Running time of truth update with varying number of objects.

Similar observations can be made in Fig. 5. For the procedure of weight update, since more $Dist_k$ need to be encrypted with the increasing number of devices, the run time of all schemes grows linearly. In the procedure of truth update, as all schemes need to perform more aggregation operations to calculate $\sum_{k=1}^{K} x_m^k \cdot w_k$ and $\sum_{k=1}^{K} w_k$, the run time forms a linear relation with the number of devices. Based on these results, we can conclude that LPTD schemes are more efficient than existing solutions.

Figure 5: (a) Running time of weight update with varying number of devices. (b) Running time of truth update with varying number of devices.
7. Related work

A number of truth discovery schemes have been studied previously [4, 5, 6, 21, 22, 23, 24, 25, 26, 27], and hence can become an attractive solution for CIoT applications. Among them, CRH [4], AcuSim [5], TruthFinder [25] are some representative schemes which can provide more reliable results by considering device reliability in the aggregation process compared to the traditional voting or averaging approaches. However, these systems fail to take into consideration important privacy issues, which may disclose some personal sensitive information [28, 29, 30].

To protect devices’ privacy, many privacy-preserving approaches have been proposed recently. For example, anonymization based schemes are presented by [14, 31] to protect devices’ private information. However, these cannot be used in truth discovery scenarios, since they are not designed to protect the data values. Cryptography based schemes are another option to effectively protect devices’ privacy. For example, Miao et al. [7] proposed a privacy-preserving truth discovery scheme by utilizing the threshold Paillier cryptosystem to protect users’ privacy. However, their system is based on the assumption that there is no collusion between the cloud server and other parties. When such collusion occurs, the devices’ privacy can be inferred. Moreover, cryptography schemes are not efficient, especially considering the battery and computation limitation of mobile devices. Another scheme [27] integrated the incentive with truth discovery approaches. However, the platform is trusted in their scheme which may impede its wide adoption. To improve the efficiency, Xu et al. [8] proposed an efficient and privacy-preserving truth discovery scheme by using an additive homomorphic data aggregation technique. Specifically, each device is assigned a random value and secret key, and the sensory data is blinded before delivering to the cloud. Finally, the authorized receivers can use the secret key and the aggregated random values to decrypt the ciphertexts. However, in real-life CIoT applications, device failure or missing data is a common issue. In such cases, this scheme does not work, since some of the random values are missing.
Miao et al. [12] further proposed a lightweight and privacy-preserving truth discovery scheme by using two non-colluding cloud platforms. Specifically, each device is assigned random values to perturb the sensory data, weighted data, and the weight. All these perturbed data is submitted to a cloud $S_1$, while the perturbation values are submitted to another cloud $S_2$. These two clouds can cooperatively compute the truths without disclosing the sensitive information. However, similar to [8], their scheme cannot achieve fault-tolerance. Moreover, if $S_2$ eavesdrops the devices, it may decrypt the sensitive data by using the corresponding perturbation value. Finally, none of these schemes can resist external false data injection attacks.

8. Conclusion

This article proposes two lightweight and privacy preserving truth discovery schemes for CIoT. LPTD-I is able to use fog nodes to resist false data injections, and achieve efficient truth discovery with minimal overhead. LPTD-II is an extension to previous scheme, which in addition to attack resistance and efficient privacy preservation, provides fault tolerance. Detailed security analysis shows that the proposed LPTD schemes are secure under a comprehensive security model. Experimental evaluation shows significant reduction in computation times as compared to other schemes.

ACKNOWLEDGMENT

This research is supported by the National Natural Science Foundation of China (Grant Nos. 61402037, 61272512).

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PTBI: An Efficient Privacy-Preserving Biometric Identification Based on Perturbed Term in the Cloud

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Abstract—Biometric identification has been increasingly popular to authenticate individuals’ identities. For efficiency and economic savings, biometric data owners are motivated to outsource the identification to a third party, which brings a tradeoff between the efficiency and privacy protection. In this paper, we propose a new privacy-preserving biometric identification scheme which can release the database owner from heavy computation burden. In the proposed scheme, we design a new biometric data encryption and matching algorithm by exploiting inherent structures of biometric data and introducing perturb terms. A through analysis indicates that our scheme is secure and offers a higher level of privacy protection than existing biometric identification outsourcing works. The experimental results further show that our proposed scheme meets the efficiency need well.

Index Terms—Biometric identification; data outsourcing; privacy-preserving; cloud computing.

I. INTRODUCTION

THIS Biometric identification is a task to authenticate users’ identities with biometric data, which includes fingerprints, irises, facial patterns, etc. Compared with the traditional authentication methods such as passwords and identification cards, biometric identification searches the traits collections to find the best match for a given biometric trait [1]. As biometric sensors (e.g., fingerprint sensors, etc.) are becoming smaller and cheaper, automatic identification based on biometric data is becoming an attractive alternative to the traditional authentication methods of identification [7].

A typical biometric identification system consists of two parties including a database owner and users. The database owner stores a set of biometric data and users can submit a candidate biometric trait to the database owner for identification. To release the database owner from the expensive local storage and heavy computation burden, more and more companies and governments are motivated to upload their data to the cloud server for economic and storage savings [2]. When introducing cloud to the system, sensitive biometric data has to be encrypted before outsourcing. Specifically, the database owner encrypts the biometric data and then sends it to the cloud server. Whenever a user (e.g., a partner of the national apartments such as a bank) wants to identify an individual’s (e.g., a banker) identity, the bank will submit a query to the database owner. Upon receiving the query, the database owner executes the query encryption and further turns to the cloud server for identification.

However, realizing such a biometric identification outsourcing system is challenging considering the requirements of data privacy and matching efficiency. Several solutions [3], [4], [6], [9], [10], [11], [12], [14], [15], [16] have been proposed to try to achieve good tradeoff between efficiency and privacy protection. However, most of them suffer from efficiency issues (e.g., based on complex homomorphic encryption for example) or security drawbacks (e.g., not secure or secure but under weak attack models). In [11] and [16], homomorphic encryption and obvious transfer were utilized to protect biometric data privacy. However, with computation costs introduced, their schemes failed to support a large database. Recently, Huang et al. [3] proposed a privacy-preserving biometric identification scheme based on homomorphic encryption and garbled circuits. Compared with [11] [16], Huang et al.’s scheme can support a larger database up to 1GB. However, as a secure two-party system, their scheme cannot be applied in the outsourcing model directly. To suit the outsourcing demands, Yuan and Yu [4] proposed a cloud-based privacy-preserving biometric identification scheme. However, Zhu et al. [5] and Wang et al. [6] pointed out that Yuan and Yu’s scheme was not secure. To solve the drawbacks, Wang et al. [6] moreover proposed a biometric identification scheme by introducing random diagonal matrices. Note that Wang et al.’s scheme was based on a weaker attack model compared with [4]. If the attacker has the ability to collude with the cloud server, simultaneously observe some biometric data and queries at the same time, their scheme can be completely broken.

In this paper, for the first time, we propose a scheme which achieves a higher level of privacy protection than existing works and obtains high identification efficiency. Specifically, in our scheme, the pre-processed biometric data is encrypted and outsourced to the cloud server. When a user needs to identify a biometric trait, the user submits the query to the database owner where the query will be extended and encrypted. After receiving the query, the cloud server searches the encrypted database and returns the index of the matching ciphertext to the database owner, where the FingerCodes’ Euclidean distance can be efficiently computed. Different from previous works, we exploit inherent structures of the biometric data and introduce some perturbed terms into the data before performing encryption. Our main contributions can be summarized as follows:

- This paper proposes efficient privacy-preserving biometric identification solutions for high privacy requirements.
- We enable our scheme to securely outsource the biometric...
This paper proposes an efficient biometric data encryption and secure outsourced matching scheme. To release the database owner from the tremendous computation burden, we use random matrices and vectors to execute the data encryption and matching. Compared with the works [4], [6] utilizing the same encryption method, the proposed scheme is tailored to suit a higher level of privacy and efficiency requirement. For example, when encrypting the biometric data, we execute fewer matrices multiplication operations than [4] which resulting in less data encrypting time. And since we transmit the matrix multiplications to vector-matrix multiplications, the identification time in our scheme can significantly save as much as 73.4% cost than [6].

The remainder of this paper is organized as follows: Section II presents the problem formulation, including system model, threat model and our design goals. In Section III, we provide our construction, including two schemes with correctness and security analysis followed. Performance analysis is presented in Section IV. In Section V, we give the related work and our conclusion is presented in Section VI.

II. PROBLEM FORMULATION

A. System Model

Considering a cloud-based biometric identification system involves three different entities, as shown in Fig.2: the database owner, users and the cloud server. The database owner outsources the encrypted database to the cloud server. When identifying a user’s identify, a query will be transmitted to the database owner and further uploaded to the cloud server. More specifically, the database owner owns a set of biometric data (e.g., fingerprints, voice patterns, facial patterns, etc.). For convenience of database search, the database owner will build an index I for each biometric data. Then the index and the encrypted biometric data are both outsourced to the cloud server. When identifying a candidate biometric data, a query is submitted to the database owner by a user. After receiving the query, the database owner executes the encryption and then uploads the ciphertext to the cloud server. Upon receiving the ciphertext, the cloud server is responsible to find the best match and returns the corresponding index to the database owner. Subsequently, the database owner computes the Euclidean distance between the candidate biometric data and the plaintext corresponding to the returned index. Finally, the database owner checks the distance with the defined threshold and returns the final result to the user.

We assume the biometric data (e.g., fingerprint data) either in the user side or the database owner side has been processed such that the representation of the biometric data is fit for the encryption and matching. In this work, we focus on fingerprint identification and obtain the fingerprint data following the feature extraction algorithm [7]. In our scheme, a FingerCode with n elements (typically n = 640) is utilized to represent a fingerprint image.

Given two FingerCodes $b_1 = [b_{11}, b_{12}, \ldots, b_{1n}]$ and $b_2 = [b_{21}, b_{22}, \ldots, b_{2n}]$, their Euclidean distance is defined as:

$$dist_{12} = \sqrt{\sum_{j=1}^{n} (b_{1j} - b_{2j})^2} \quad (1)$$

If the Euclidean distance is below the defined threshold, the two FingerCodes can be considered from the same person. Therefore, the process of identifying a candidate biometric data can be described as follows: candidate FingerCodes encryption, secure Euclidean distance computation, best match finding and result retrieval. The database owner executes the first and the last steps, and others are executed on the cloud server side. In our cloud-based biometric identification scheme, to improve the efficiency, the time-consuming matching operations are outsourced to the cloud server.
propose a privacy-preserving efficient biometric identification under Level-II attack. This scheme is named as PTBI-I. Then, we present an enhanced scheme named PTBI-II which can achieve security under Level-III attack.

A. PTBI-I: The Basic Scheme

1) Biometric Database Encryption Phase: As described in Section II-A, the fingerprint image is assumed to be pre-processed using the extraction algorithm and generated as a FingerCode \( b_i \). The FingerCode \( b_i = [b_{i1}, b_{i2}, \ldots, b_{in}] \) is an \( n \)-dimension vector with each element’s size \( l \) bits (typically, \( n = 640 \) and \( l = 8 \)). To facilitate the identification matching, the FingerCode is extended to \((n+2)\)-dimension vector as \( B_i \), where the \((n+1)\)-th element is set to \(-0.5(b_{i1}^2 + b_{i2}^2 + \cdots + b_{in}^2)\) and the \((n+2)\)-th dimension is 1. For biometric data protection, the encryption operations are performed as follows:

Step 1: The system owner randomly generates secret keys involving two \((n+2)\times(n+2)\) invertible matrices as \( \{M_1, M_2\} \) and one \( (n+2)\)-dimension vector as \( H \), where each element in the secret keys is a random value with the same size as the elements in the FingerCode.

Step 2: For protection of each extended FingerCode \( B_i \), a random \((n+2)\times(n+2)\) matrix \( D_i \) is generated to hide the biometric data as:

\[
D_i = \begin{bmatrix}
A_{11}b_{11} & A_{12}b_{12} & \cdots & A_{1(n+2)}b_{1n} \\
A_{21}b_{12} & A_{22}b_{12} & \cdots & A_{2(n+2)}b_{1(n+2)} \\
\vdots & \vdots & \ddots & \vdots \\
A_{(n+2)1}b_{(n+2)} & A_{(n+2)2}b_{(n+2)} & \cdots & A_{(n+2)(n+2)}b_{(n+2)}
\end{bmatrix}
\]

where \( A_i = [A_{i1}, A_{i2}, \ldots, A_{i(n+2)}] \) (\( i \in [1, n+2] \)) is set as a random vector, and satisfies the requirement \( A_i \times H^T = 1 \). More specifically, FingerCode \( B_i^T \) can be recovered by using the secret key \( H \) and the matrix \( D_i \) as \( D_i \times H^T = B_i^T \).

Step 3: After hiding the FingerCode, the database owner further executes encryption as follows:

\[
C_i = M_1^{-1} \times D_i \times M_2
\]

After encryption, the database owner builds an index \( I_i \) and associates it with the FingerCode \( b_i \) and its encrypted form \( C_i \). Then, the tuple \( \{C_i, I_i\} \) is uploaded to the cloud server for storage.

2) Biometric Data Matching Phase: In this phase, the query will be encrypted. Before executing query encryption, we first give the definition of the secure Euclidean distance which serves as the similarity measurement in our scheme.

Definition 1: secure Euclidean distance

The FingerCode which has the minimum Euclidean distance with the query is needed to be figured out. However, it is not necessary to compute all Euclidean distances to identify the closest one. For example, given two FingerCodes \( b_1, b_2 \)
and a query \( b_c \). Their secure Euclidean distance \( S_{12} \) can be computed as follows:

\[
S_{12} = dist_{ic}^1 - dist_{ic}^2 = \sum_{j=1}^{n} (b_{ij} - b_{c})^2 - \sum_{j=1}^{n} (b_{lj} - b_{c})^2 = \sum_{j=1}^{n} (b_{ij}^2 - b_{c}^2) + 2\sum_{j=1}^{n} (b_{lj} - b_{ij})b_{c}
\]  

Equation (4)

Base on the equation 4, the FingerCode which has smaller distance with the query can be identified by checking the positive or negative of \( S_{12} = \sum_{j=1}^{n} (b_{ij} - b_{c})^2 + 2\sum_{j=1}^{n} (b_{lj} - b_{ij})b_{c} \) without knowing the Euclidean distance.

**Step 4:** When identifying a candidate FingerCode, a user submits a query FingerCode to the database owner. The database owner then extends the query to \( B_c = [b_{c1}, b_{c2}, \ldots, b_{cn}, 1, r_c] \), where \( r_c \) is a random positive value. Note that, \( r_c \) is chosen differently. Then, the database owner executes the following operation:

\[
C_F = B_c \times M_1
\]  

Equation (5)

After encrypting the query, the database owner further encrypts \( H \) as:

\[
C_H = M_2^{-1} \times H^T
\]  

Equation (6)

where \( M_2^{-1} \) is the inverse matrix of \( M_2 \).

The tuple \( \{C_F, C_H\} \) is then uploaded to the cloud server for identification.

**Step 5:** Upon receiving the encrypted query, the cloud server begins to compute the similarity between the query and the encrypted biometric data. Let \( P_i \) denote the similarity score, the computation of \( P_i \) is executed as follows:

\[
P_i = C_F \times C_i \times C_H = B_c \times M_1 \times M_2^{-1} \times D_i \times M_2 \times M_2^{-1} \times H^T = B_c \times B_i^T = \sum_{j=1}^{n} b_{c} \times b_{ij} + r_c
\]  

Equation (7)

Then the cloud server ranks similarity score \( P_i \), and returns the top-1 ranked index to the database owner.

3) **Final Matching Computation Phase:** We should note that the Index returned from the cloud server represents the FingerCode which has the minimum Euclidean distance with the query in the database. Since the exact Euclidean distance is not known, the database owner needs to compute the exact distance between \( b_i \) and \( b_c \) as shown in equation 1 to identify if these two FingerCodes belong to the same person.

**Step 6:** After receiving the Index \( I_i \), the database owner gets the corresponding biometric data \( b_i \) and computes the Euclidean distance \( dist_{ic} \) between \( b_i \) and \( b_c \). Then, by checking \( dist_{ic} < \text{defined threshold} \), \( b_c \) is identified, otherwise, denied. Finally, the database owner returns the final result to the user.

**Correctness Analysis** As shown in equation 7, \( P_i \) is an integer and the sign of \( P_i - P_z \) can be computed as follows:

\[
P_i - P_z = (\sum_{j=1}^{n} b_{ij} \times b_{c}) - (\sum_{j=1}^{n} b_{rj} \times b_{c}) = (\sum_{j=1}^{n} b_{ij} \times b_{c}) - 0.5(\sum_{j=1}^{n} b_{rj}^2 + r_c) - (\sum_{j=1}^{n} b_{rj} \times b_{c}) = 0.5(dist_{ic}^2 - dist_{ic}^2) = -0.5S_{ic}
\]  

Equation (8)

According to the Definition 1, \( S_{ic} \) is an representation of the secure Euclidean distance. The cloud server can get the similarity by checking the sign of \( P_i - P_z \). If \( P_i - P_z > 0 \), the cloud server gets \( dist_{ic} > dist_{ic} \) which indicates \( b_i \) better matches the query. Otherwise, cloud gets \( dist_{ic} < dist_{ic} \). Therefore, the largest similarity score indicates the minimum Euclidean distance. After repeating the matching process for all the encrypted database, the cloud server only needs to find the largest similarity score and returns the corresponding index.

**Security Analysis**

**Theorem 1.** PTBI-I scheme is secure under Level-II attack.

**Proof of Theorem 1.** See Appendix A. \( \square \)

**B. PTBI-II: The Enhanced Scheme**

PTBI-I scheme achieves identification efficiency and also provides privacy protection under Level-II attack, but it will lead to privacy leakage under Level-III attack. Specifically, the cloud server can get all the values of similarity scores according to the equation \( P_i = C_F \times C_i \times C_H \). When the attacker has the ability to observe \( < b_i, c_i > (1 \leq i, z \leq m) \) and construct query \( b_c, r_c \), can be recovered as \( P_i = \sum_{j=1}^{n} b_{ij} \times b_{c} - 0.5 \sum_{j=1}^{n} b_{rj}^2 \). Following the same way, the attacker can construct query \( b'_{l} \) and get the encryption random \( r_{l} \), where \( l \in [1, t] \). After that, for unknown biometric data \( b_{kc} \), the cloud server can compute \( b_{hc} \) according to the equation \( P_k = \sum_{j=1}^{n} b_{ik} \times b_{kj} - 0.5 \sum_{j=1}^{n} b_{rj}^2 + r_{l} \). To achieve higher level of privacy protection, we further propose an enhanced scheme to introduce more randomness when encrypting the biometric data.

The key difference between the PTBI-I and PTBI-II scheme is that the database owner introduces some randomness in the similarity score. Besides introducing the randomness in the query, the database owner inserts a random variable into each biometric data. All the vectors are extended to \((n + 3)\)-dimension instead of \((n + 2)\) and all the matrices are extended to \((n + 3) \times (n + 3)\). More specifically, \( b_i = [b_{i1}, b_{i2}, \ldots, -0.5 \sum_{j=1}^{n} b_{rj}^2, 1, \varepsilon_i] \), \( b_c = [b_{c1}, b_{c2}, \ldots, 1, r_c, 1] \), where \( \varepsilon_i \) is a random variable.
The remaining operations for the biometric database encryption phase, biometric data matching phase are the same as PTBI-I scheme.

Correctness Analysis In PTBI-II scheme, the cloud server computes the similarity score as \( P_i = \sum_{j=1}^{n+1} b_{ij} \times b_{ij} + r_c + \varepsilon_i \). Because randomness \( \varepsilon_i \) is introduced as a part of the similarity score, the search result may not be as accurate as that in PTBI-I scheme. However, considering the obvious differences among the different FingerCodes, if \( \varepsilon_i \) is controlled in an appropriate scope, the search result can be considered as the expected one. In this scheme, we let \( \varepsilon_i \) follow a normal distribution \( N(0, \sigma^2) \).

Security Analysis Apparently, the introduction of the random variable \( \varepsilon_i \) will not compromise the security requirements of PTBI-I, thus PTBI-II is still secure under Level-II attack. As for Level-III attack, we have the following theorem.

**Theorem 2.** PTBI-II scheme is secure under the Level-III attack.

**Proof of Theorem 2.** See Appendix B.

Moreover, we compare the security with other two schemes in terms of our threat models. In Table I, we can see only our PTBI-II scheme achieves security under all three level attacks.

### IV. Performance Analysis

To evaluate the performance of our schemes, we implement PTBI-I and PTBI-II schemes by using C language. The cloud server is set up with 2 nodes each with 6-core 2.10 GHz Intel(R) Xeons(R) CPU E5-2620 V2 and 32 GB of memory. For the database owner, we use a laptop with Intel(R) Core(TM) 2.40GHz CPU and 8 GB of memory. We randomly generate 640-dimensional vectors as the FingerCodes to construct the biometric database and randomly select some of the FingerCodes as the queries to complete the identification task.

#### A. Complexity Analysis

Before implementing our scheme, we first analyze the complexity of our PIBI-I scheme and PTBI-II scheme. As described in Section III, our schemes can be decomposed into three stages. In stage 1, the whole biometric database is encrypted. For each biometric data, the database owner executes matrix multiplication operations. Note that, each matrix multiplication has a time complexity of \( O(n^3) \), where \( n \) is the dimension of the FingerCode. We assume there exists \( m \) FingerCodes needed to be encrypted, the total complexity in stage 1 is \( O(m \times n^3) \). In stage 2, a query is submitted to the database owner. To execute the query encryption, the database owner performs vector-matrix multiplication, which costs \( O(n^2) \). Similar to the previous analysis, the encryption of \( H \) also costs \( O(n^2) \). For the cloud server side, the operation of matrix multiplying vectors is needed to process the similarity score computation, which costs \( O(n^2) \). Assuming there exists \( m \) encrypted biometric data, to figure out the FingerCode which has the minimum Euclidean distance with the query, the total computation complexity is \( O(m \times n^2 \times m \log m) \). Note that, the identification phase can be executed in parallel on the cloud server, which can ensure our scheme is efficient. In stage 3, the database owner computes the Euclidean distance between the query and the FingerCode according to the returned index, which costs \( O(n) \). As shown in the TABLE II, compared with other schemes, the complexity in our scheme is the lowest in all stages.

#### B. Experimental Evaluation

**Preparation phase:** Fig.3 and Fig.4 show the time cost and the bandwidth consumption in the preparation phase. Considering the biometric data encryption is a one-time cost, the preparation time in all schemes grow linearly as the number of FingerCodes increases. As shown in Fig.3, the preparation time is almost the same as PTBI-I, PTBI-II and Wang et al.’s scheme, which confirms the theoretical analysis in TABLE II. As Yuan and Yu’s scheme executes more encryption operations, it takes more time than the other three schemes. The bandwidth consumptions of all four schemes, as shown in Fig.4, are almost the same. Note that this is a one-time cost which can be bypassed by using hard disk drive transmission services to save bandwidth consuming.

![Fig. 3. Time costs for different number of FingerCodes in preparation phase.](image1)

![Fig. 4. Bandwidth costs for different number of FingerCodes in preparation phase.](image2)
TABLE I
SECURITY COMPARISON WITH OTHER SCHEMES.

| Schemes                | Level-I attack | Level-II attack | Level-III attack |
|------------------------|----------------|-----------------|-----------------|
| Yuan and Yu’s scheme [5] | Yes            | Yes             | No              |
| Wang et al.’s scheme [7] | Yes            | Yes             | No              |
| PTBI-I scheme          | Yes            | Yes             | No              |
| PTBI-II scheme         | Yes            | Yes             | No              |

TABLE II
A SUMMARY OF COMPLEXITY COSTS: \( m \) DENOTES THE NUMBER OF THE BIOMETRIC DATA; \( n \) DENOTES THE DIMENSION OF THE FINGERCODE, \( n \ll m \).

| Schemes                | Preparation Phase | Query Encryption | Identification Phase | Retrieval |
|------------------------|-------------------|------------------|----------------------|----------|
| Yuan and Yu’s scheme [5] | \( O(mn^3) \)     | \( O(n^4) \)     | \( O(mn^2 + m\log m) \) | \( O(n) \) |
| Wang et al.’s scheme [7] | \( O(mn^3) \)     | \( O(n^4) \)     | \( O(mn^2 + m\log m) \) | \( O(n) \) |
| PTBI-I scheme          | \( O(mn^3) \)     | \( O(n^4) \)     | \( O(mn^2 + m\log m) \) | \( O(n) \) |
| PTBI-II scheme         | \( O(mn^3) \)     | \( O(n^4) \)     | \( O(mn^2 + m\log m) \) | \( O(n) \) |

Identification phase: Fig.5 and Fig.6 show the time cost and the bandwidth consumption in the identification phase. As shown in Fig.5, since PIBI-I and PTBI-II have the same complexity costs and computation operations, the time costs are almost the same. As Yuan and Yu’s scheme has more vector multiplication operations, it takes a little more time than ours. Compared with Wang et al.’s scheme, since the matrix multiplications are transmitted to vector-matrix multiplications when computing the similarity scores, our schemes can save as much as 73.4% time cost. For bandwidth consumption of a query, as shown in Fig.6, the growth of the number of the FingerCodes will not influence the cost of our PTBI schemes, which is about 1.25 KB. Nevertheless, the bandwidth consumption in [4] and [6] is also constant, but costs about 400 KB. The reason is that when performing the identification, our schemes only need to transmit two vectors while other two schemes need to upload a matrix.

Fig. 5. Time costs for different number of FingerCodes in identification phase.

Fig. 6. Bandwidth costs for different number of FingerCodes in identification phase.

V. RELATED WORK

Recently, privacy protection and efficiency models on biometric identification have been studied well [3], [4], [6], [9], [10], [11], [12], [14], [15], [16], most of which are trying to find a tradeoff between the efficiency and privacy protection. Wang and Hatzinakos [9] proposed a privacy-preserving face recognition scheme. By measuring the similarity between stored index numbers vectors, the expected one can be identified. Wong and Kim [10] presented a privacy-preserving biometric identification scheme. However, their scheme is computationally infeasible if a malicious client impersonates an honest user. To enhance privacy protection, in [11], a new privacy-preserving biometric identification protocol is proposed by Barni et al. By using homomorphic encryption, their scheme can guarantee biometric data privacy. Nevertheless, to compute distances between the query with all matched fingerprints, heavy computation burden will be introduced for a large biometric database. Osadchy introduced a privacy-preserving scheme for identification with face image utilizing oblivious transfer [16]. It can also achieve privacy protection in a higher level, but still suffers from efficiency problem. To better balance the efficiency and privacy protection, Huang et
al. [3] and Blanton et al. [12] proposed biometric identification schemes which combine homomorphic encryption and garbled circuits. Specifically, they use homomorphic encryption to compute Euclidean distance and garbled circuits to find the minimum distance. However, as a client leading system, their schemes need to transmit the entire encrypted database from the database owner to the client side for each query. Similar to the former solutions [9], [10], [11], their schemes are still two-party protocols, which heavily rely on the hardware performance for both owner side and client side. To omit the local hardware limitations, it is considered to be a promising future to outsource the identification operations to a third party (e.g., the cloud server) and many solutions [4] [6] [13] [14] [15] are proposed. Wong et al. [13] proposed a kNN-based identification scheme which provides a new way to securely search for the encrypted database. Hu et al. [14] proposed a new outsourcing scheme which can achieve the database security and privacy-preserving outsourcing separately. However, all these schemes are based on the assumption that there is no collusion between the third outsourcing party and the client side, which may produce privacy disclosure problems. To achieve a higher security level, a secure kNN query scheme is proposed by Elmehdwi et al. [15]. But their scheme suffers from the problems such as leakage of secret keys and low efficiency.

In 2013, Yuan and Yu [4] developed an efficient privacy-preserving biometric identification in cloud computing. They use matrix to design encryption scheme in the outsourcing model and the performance indicates that their computational costs are several magnitudes lower than the previous works. They claimed that their scheme can resist the known-plaintext attack (KPA) and the chosen-plaintext attack (CPA). Unfortunately, Zhu et al. [5] and Wang et al. [6] pointed out that their scheme can be completely broken if there exists collusion between the client side and the cloud server. Moreover, Wang et al. [6] presented a new cloud-based practical privacy-preserving outsourcing of biometric identification scheme by introducing more random diagonal matrices to resist KPA and CPA attacks. However, Wang et al.’s scheme is based on a weaker attack model than [4]. Specifically, they assume the attacker cannot has the ability to collude with the cloud server, simultaneously observe some plaintexts of the database and construct queries at the same time. They claim that this attack is too strong that there exists no effective schemes which can defend against this attack. In this paper, we omit this assumption by introducing perturbed terms to each biometric data. Compared with previous works, our scheme achieves a higher level of privacy protection and gives consideration well to the efficiency.

VI. CONCLUSIONS

In this paper, for the first time, our proposed scheme achieves a higher level of privacy protection and identification efficiency than state-of-art biometric identification outsourcing schemes. Among various encryption methods for biometric traits, we utilize matrix and perturbed terms to protect data privacy and design a new encryption scheme to efficiently find the best match in the cloud server. The security and experiments analysis indicate that our scheme can give consideration well to the privacy protection and efficiency. In future, we will work on designing more efficient privacy-preserving biometric identification schemes.
where there are \( t \) equations with strictly \( t + n + 3 \) unknowns. Thus, the attacker cannot compute \( M_j^{-1} \), which means \( M_1^{-1} \) cannot be recovered.

We further consider the attacker can be a valid user and construct query \( b_c \). Note that \( b_c \) is an \( n \)-dimension vector \((B_c)\) is the encrypted form with \((n + 3)\) elements, where the last three are set as \( 1 \), random variable \( r_c \) and \( 1 \). According to the knowledge of linear algebra, there is at most \( n \) linearly independent \( \{b_{c1}, b_{c2}, \ldots, b_{cn}\} \) can be generated to represent \( b_c \) as

\[
b_c = x_1 b_{c1} + x_2 b_{c2} + \cdots + x_n b_{cn} \quad (12)
\]

where \( \{x_1, x_2, \cdots, x_n\} \) is a set of coefficients. After \( b_c \) is extended as \( B_c \), the attacker has

\[
B_c = x_1 B_{c1} + x_2 B_{c2} + \cdots + x_n B_{cn} \quad (13)
\]

Thus, \( C_F \) can be represented as

\[
C_F = (x_1 B_{c1} + x_2 B_{c2} + \cdots + x_n B_{cn}) M_1
\]

(14)

From this equation, we can see at most \( n \) linearly independent pairs of \( (B_{cj}, C_{Fj}) \) can be built by an ideal attacker, where \( 1 \leq j \leq n \). Without loss of generality, we assume the attacker chooses a basis \( B_{c1} = [1, 0, 0, \ldots , 0, 1, r_c, 1], B_{c2} = [0, 1, 0, \ldots , 0, 1, r_c, 1], \ldots, B_{cn} = [0, 0, \ldots , 1, 1, r_c, 1] \) in the \( n \)-dimensional vector space. Then the attacker has:

\[
C_{F1} = B_{c1} M_1
\]

(15)

\[
\begin{bmatrix}
p_{11} & p_{12} & \cdots & p_{1(n+1)} & p_{1(n+2)} & p_{1(n+3)} \\
p_{21} & p_{22} & \cdots & p_{2(n+1)} & p_{2(n+2)} & p_{2(n+3)} \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\
p_{(n+1)1} & p_{(n+1)2} & \cdots & p_{(n+1)(n+1)} & p_{(n+1)(n+2)} & p_{(n+1)(n+3)} \\
p_{(n+2)1} & p_{(n+2)2} & \cdots & p_{(n+2)(n+1)} & p_{(n+2)(n+2)} & p_{(n+2)(n+3)} \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\
p_{(n+3)1} & p_{(n+3)2} & \cdots & p_{(n+3)(n+1)} & p_{(n+3)(n+2)} & p_{(n+3)(n+3)} \\
\end{bmatrix}
\]

\[
= [p_{11} + p_{1(n+1)} + r_c p_{1(n+2)} + p_{1(n+3)}; p_{21} + p_{2(n+1)} + r_c p_{2(n+2)} + p_{2(n+3)}; \ldots; p_{(n+1)1} + p_{(n+1)(n+1)} + r_c p_{(n+1)(n+2)} + p_{(n+1)(n+3)}; p_{(n+2)1} + p_{(n+2)(n+1)} + r_c p_{(n+2)(n+2)} + p_{(n+2)(n+3)}; \ldots; p_{(n+3)1} + p_{(n+3)(n+1)} + r_c p_{(n+3)(n+2)} + p_{(n+3)(n+3)}]
\]

\[
C_{F} = B_{cn} M_1
\]

(16)

The attacker will try to recover \( M_1 \), e.g., \( q_{ij} \). For example, the attacker chooses \( C_{F1} \), and has

\[
\begin{align*}
\dot{C}_{(F1)1} &= p_{11} + p_{(n+1)1} + r_c p_{(n+2)1} + p_{(n+3)1} \\
\dot{C}_{(F1)2} &= p_{12} + p_{(n+1)2} + r_c p_{(n+2)2} + p_{(n+3)2} \\
\vdots \\
\dot{C}_{(F1)(n+3)} &= p_{1(n+3)} + p_{(n+1)(n+3)} + r_c p_{(n+2)(n+3)} + p_{(n+3)(n+3)} \\
\end{align*}
\]

where there are \( n + 3 \) equations with \( 4(n + 3) + 1 \) unknowns. Thus, the ideal attacker cannot recover \( M_1 \).

As for the matching process in the cloud server, according to the equation 7, in PTBI-II scheme, the \textit{similarity score} is computed as follows:

\[
P_i = C_F 	imes C_1 	imes C_H = \sum_{j=1}^{n} b_{ij} b_{cj} - 0.5 \sum_{j=1}^{n} b_{ij}^2 + r_c + \varepsilon_i
\]

(17)

the attacker can use the same attack methods to bypass the computation of the secret keys and derive the unknown query FingerCode directly from other honest users. By selecting \( t \) biometric data \( \{b_{1}, b_{2}, \ldots, b_{t}\} \) and corresponding ciphertexts \( \{C_{1}, C_{2}, \ldots, C_{t}\} \), the attacker has:

\[
\begin{align*}
\dot{P}_1 &= \sum_{j=1}^{n} b_{1j} b_{cj} - 0.5 \sum_{j=1}^{n} b_{1j}^2 + r_c + \varepsilon_1 \\
\dot{P}_2 &= \sum_{j=1}^{n} b_{2j} b_{cj} - 0.5 \sum_{j=1}^{n} b_{2j}^2 + r_c + \varepsilon_2 \\
&\vdots \\
\dot{P}_t &= \sum_{j=1}^{n} b_{tj} b_{cj} - 0.5 \sum_{j=1}^{n} b_{tj}^2 + r_c + \varepsilon_t \\
\end{align*}
\]

Following the same analysis as above, there are \( t \) equations with \( t + 1 \) unknowns. Thus, the ideal attacker cannot recover the query as well.

We then consider the attacker can be a valid user and recover the unknown biometric data \( b_c \) by constructing query \( b'^{t}_{j} (t \in [1, t]) \). Following the same analysis, after constructing \( t \) queries, the attacker has:

\[
\begin{align*}
\dot{P}_1 &= \sum_{j=1}^{n} b_{kj} b'^{t}_{j} - 0.5 \sum_{j=1}^{n} b_{kj}^2 + r_c + \varepsilon_k \\
\dot{P}_2 &= \sum_{j=1}^{n} b_{kj} b'^{t}_{j} - 0.5 \sum_{j=1}^{n} b_{kj}^2 + r_c + \varepsilon_k \\
&\vdots \\
\dot{P}_t &= \sum_{j=1}^{n} b_{tkj} b'^{t}_{j} - 0.5 \sum_{j=1}^{n} b_{tkj}^2 + r_c + \varepsilon_k \\
\end{align*}
\]

where there are \( t \) equations with \( t + 1 \) unknowns, the attacker cannot recover the unknown biometric data as well.

Based on the above analysis, the attacker cannot access the private biometric data or recover the secret keys by building enough knowledge. Therefore, PTBI-II scheme is secure under Level-III attack.

ACKNOWLEDGMENT

This research is supported by the National Natural Science Foundation of China (Grant Nos. 61402037, 61272512).

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