An Efficient and Privacy-Preserving Biometric Identification Scheme in Cloud Computing

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ABSTRACT Biometric identification has become increasingly popular in recent years. With the development of cloud computing, database owners are motivated to outsource the large size of biometric data and identification tasks to the cloud to get rid of the expensive storage and computation costs, which however brings potential threats to users’ privacy. In this paper, we propose an efficient and privacy-preserving biometric identification outsourcing scheme. Specifically, the biometric data is encrypted and outsourced to the cloud server. To execute a biometric identification, the database owner encrypts the query data and submits it to the cloud. The cloud performs identification operations over the encrypted database and returns the result to the database owner. A thorough security analysis indicates the proposed scheme is secure even if attackers can forge identification requests and collude with the cloud. Compared with previous protocols, experimental results show the proposed scheme achieves a better performance in both preparation and identification procedures.

I. INTRODUCTION

Biometric identification has raised increasingly attention since it provides a promising way to identify users. (e.g., fingerprints, irises, voice patterns, facial patterns etc.). Compared with traditional authentication methods based on passwords and identification cards, biometric identification is considered to be more reliable and convenient [1]. Additionally, biometric identification has been widely applied in many fields by using biometric traits such as fingerprint [2], iris [3], and facial patterns [4], which can be collected from various sensors [5]–[9].

In a biometric identification system, the database owner such as the FBI who is responsible to manage the national fingerprints database, may desire to outsource the enormous biometric data to the cloud server (e.g., Amazon) to get rid of the expensive storage and computation costs. However, to preserve the privacy of biometric data, the biometric data has to be encrypted before outsourcing. Whenever a FBI’s partner (e.g., the police station) wants to authenticate an individual’s identity, he turns to the FBI and generates an identification query by using the individual’s biometric traits (e.g., fingerprints, iris, voice patterns, face patterns etc.).

Then, the FBI encrypts the query and submits it to the cloud to find the close match. Thus, the challenging problem is how to design a protocol which enables efficient and privacy-preserving biometric identification in the cloud computing.

A number of privacy-preserving biometric identification solutions [10]–[17] have been proposed. However, most of them mainly concentrate on privacy preservation but ignore the efficiency, such as the schemes based on homomorphic encryption and oblivious transfer in [10], [11] for fingerprint and face image identification respectively. Suffering from performance problems of local devices, these schemes are not efficient once the size of the database is larger than 10 MB. Later, Evans et al. [12] presented a biometric identification scheme by utilizing circuit design and ciphertext packing techniques to achieve efficient identification for a larger database of up to 1GB. Additionally, Yuan and Yu [13] proposed an efficient privacy-preserving biometric identification scheme. Specifically, they constructed three modules and designed a concrete protocol to achieve the security of fingerprint trait. To improve the efficiency, in their scheme, the database owner outsources identification matching tasks to the cloud. However, Zhu et al. [18] pointed out that Yuan and Yu’s protocol can be broken by a collusion attack launched by a malicious user and cloud. Wang et al. [14] proposed the scheme CloudBI-II which used random diagonal matrices to realize biometric identification. However, their work was proven insecure in [15], [16].

In this paper, we propose an efficient and privacy-preserving biometric identification scheme which can resist the collusion attack launched by the users and the cloud.
cloud. Specifically, our main contributions can be summarized as follows:

- We examine the biometric identification scheme [13] and show its insufficiencies and security weakness under the proposed level-3 attack. Specifically, we demonstrate that the attacker can recover their secret keys by colluding with the cloud, and then decrypt the biometric traits of all users.
- We present a novel efficient and privacy-preserving biometric identification scheme. The detailed security analysis shows that the proposed scheme can achieve a required level of privacy protection. Specifically, our scheme is secure under the biometric identification outsourcing model and can also resist the attack proposed by [18].
- Compared with the existing biometric identification schemes, the performance analysis shows that the proposed scheme provides a lower computational cost in both preparation and identification procedures.

The remainder of this paper is organized as follows: section II presents the models and design goals. In section III, we provide an overview and the security analysis of the previous protocol proposed by Yuan and Yu. In section IV, we present an efficient and privacy-preserving biometric identification scheme. Security analysis is presented in section V, followed by performance evaluation in section VI. In section VII, we give the related work and we show our conclusions in section VIII.

II. MODELS AND DESIGN GOALS

This section introduces the system model, attack model, design goals and the notations used in the following sections.

A. SYSTEM MODEL

As shown in Fig.1, three types of entities are involved in the system including the database owner, users and the cloud. The database owner holds a large size of biometric data (i.e., fingerprints, irises, voice, and facial patterns etc.), which is encrypted and transmitted to the cloud for storage. When a user wants to identify himself/herself, a query request is be sent to the database owner. After receiving the request, the database owner generates a ciphertext for the biometric trait and then transmits the ciphertext to the cloud for identification. The cloud server figures out the best match for the encrypted query and returns the related index to the database owner. Finally, the database owner computes the similarity between the query data and the biometric data associated with the index, and returns the query result to the user.

In our scheme, we assume that the biometric data has been processed such that its representation can be used to execute biometric match. Without loss of generality, similar to [17], [18], we target fingerprints and use FingerCodes [19] to represent the fingerprints. More specifically, a FingerCode consists of \( n \) elements and each element is a \( l \)-bit integer (typically \( n = 640 \) and \( l = 8 \)). Given two FingerCodes \( x = [x_1, x_2, \ldots, x_n] \) and \( y = [y_1, y_2, \ldots, y_n] \), if their Euclidean distance is below a threshold, they are usually considered as a good match, which means the two fingerprints are considered from the same person.

B. ATTACK MODEL

First of all, the cloud server is considered to be “honest but curious” as described in [13]–[15], [17]. The cloud strictly follows the designed protocol, but makes efforts to reveal privacy from both the database owner and the user. We assume that an attacker can observe all the data stored in the cloud including the encrypted biometric database, encrypted queries and matching results. Moreover, the attacker can act as a user to construct arbitrary queries.

Thus, we categorize the attack model into three levels as follows:

- Level 1: Attackers can only observe the encrypted data stored in the cloud. This follows the well-known ciphertext-only attack model [20].
- Level 2: In addition to the encrypted data stored in the cloud, attackers are able to get a set of biometric traits in the database \( D \) but do not know the corresponding ciphertexts in the database \( C \), which is similar to the known-candidate attack model [21].
- Level 3: Besides all the abilities in level-2, attackers in level-3 can be valid users. Thus, attackers can forge as many identification queries as possible and obtain the corresponding ciphertexts. This attack follows the known-plaintext attack model [20].

A biometric identification scheme is secure if it can resist the level-\( \alpha \) (\( \alpha \in \{1, 2, 3\} \)) attack. Note that that if the proposed scheme can resist level-2 and level-3 attacks, it does not mean that the attacker can both be the valid user and observe some plaintexts of the biometric database simultaneously. This sophisticated attack is too strong and no effective methods is designed to defend against this kind of attack [14]. In this paper, we focus on the collusion attack between a malicious user and the cloud server. The relationship between the plaintexts of the biometric database and the ciphertexts is not known to the attacker, which is similar to the attack model proposed in [14].
C. DESIGN GOALS
In order to achieve practicality, both security and efficiency are considered in the proposed scheme. To be more specific, design goals of the proposed scheme are described as follows:

- Efficiency: Computational costs should be as low as possible at both the database owner side and the user side. To gain high efficiency, most biometric identification operations should be executed in the cloud.
- Security: During the identification process, the privacy of biometric data should be protected. Attackers and the semi-honest cloud should learn nothing about the sensitive information.

D. NOTATIONS
Here, we list the main notations used in the remaining section as follows.

- \( b_i \) – the \( i \)-th sample FingerCode, denoted as an \( n \)-dimensional vector \( b_i = [b_{i1}, b_{i2}, \ldots, b_{in}] \).

- \( B_i \) – the extended sample FingerCode of \( b_i \), denoted as an \( (n + 1) \)-dimensional vector \( B_i = [b_{i1}, b_{i2}, \ldots, b_{i(n+1)}] \), where \( b_{i(n+1)} = -0.5(b_{i1}^2 + b_{i2}^2 + \ldots + b_{in}^2) \).

- \( b_e \) – the query FingerCode, denoted as an \( n \)-dimensional vector \( b_e = [b_{e1}, b_{e2}, \ldots, b_{en}] \).

- \( B_e \) – the extended query FingerCode of \( b_e \), denoted as an \( (n + 1) \)-dimensional vector \( B_e = [b_{e1}, b_{e2}, \ldots, b_{e(n+1)}] \), where \( b_{e(n+1)} = 1 \).

- \( W \) – the secret keys collection, denoted as \( W = (M_1, M_2, M_3, H, R) \), where \( M_1, M_2 \) and \( M_3 \) are \( (n + 1) \times (n + 1) \) invertible matrices, and \( H, R \) are \( (n + 1) \)-dimensional row vectors.

- \( I_i \) – the searchable index associated with the \( i \)-th sample FingerCode \( b_i \).

- \( \Gamma \) – the query FingerCodes collection constructed by the attacker, denoted as \( \Gamma = (eb_{i1}, eb_{i2}, \ldots, eb_{i(n+1)}) \).

- \( B_e \) – the \( i \)-th extended query FingerCode constructed by the attacker, denoted as \( B_e = [eb_{i1}, eb_{i2}, \ldots, eb_{i(n+1)}] \), where \( eb_{i(n+1)} = 1 \).

III. SECURITY ANALYSIS OF YUAN AND YU’S SCHEME
In this section, we firstly describe Yuan and Yu’s scheme and then give the security analysis about their scheme. To facilitate understanding of the scheme, we use \(*\) to denote the elements multiplication operations, and use \( \times \) to denote the matrices or vectors multiplication operations.

A. YUAN AND YU’S SCHEME
Step 1: The database owner randomly generates an \((n+1) \times (n+1)\) matrix \( A \) where \( H \times A^T = 1 \) and \( A_i \) is a row vector in \( A \), \( 1 \leq i \leq (n + 1) \).

Then, the database owner generates a corresponding matrix \( D_i = [A_{i1} * b_{i1}, A_{i2} * b_{i2}, \ldots, A_{i(n+1)} * b_{i(n+1)}] \) to hide \( B_i \).

After that, the database owner performs the following operations:

\[
C_1 = M_1 \times D_i \times M_2, \quad (1)
\]
\[
C_h = H \times M_1^{-1}, \quad (2)
\]
\[
C_r = M_3^{-1} \times R^T. \quad (3)
\]

Subsequently, the database owner uploads \((C_1, C_h, C_r, I_i)\) to the cloud, where \( I_i \) is the index of \( B_i \).

Step 2: After Step 1 is executed, the cloud has stored many tuples in its database \( C \). When a user requests to identify his/her identity, he/she extends \( b_i \) and then submits the extended query \( B_e \) to the database owner. On receiving the request from the user, the database owner generates a random \((n + 1) \times (n + 1)\) matrix \( E \) such that \( E_i \times R^T = 1 \), where \( E_i \) is a row vector in matrix \( E \) and \( 1 \leq i \leq (n + 1) \).
The database owner then generates a corresponding matrix
$F_c = [E^T_1 * b_1, E^T_2 * b_2, \cdots E^T_{n+1} * b_{c(n+1)}]^T$ to hide
the query FingerCode $B_i$. The database owner then performs
the following operations:
\[
C_f = M^{-1}_2 \times F_c \times M_3
\]  

(4)

Then, the database owner uploads $C_f$ to the cloud.

Step 3: On receiving $C_f$, the cloud begins to search for the
best match. Specifically, the cloud computes $P_i = C_f \times C \times C_i$, for all encrypted biometric database to compare
the Euclidean distances between $b_i$ and $b_r$. Other details are
eliminated since they are irrelevant for the security analysis
we will describe.

B. SECURITY ANALYSIS OF YUAN AND YU’S SCHEME

In level-3 attack, an attacker has the ability to select query
FingerCodes $\Gamma$ of his/her interest as inputs and then tries to
recover the privacy of $B_i$. Specifically, the attacker can compute
the secret key $M_2$ by performing the following equation:
\[
C_f \times C_f = M^{-1}_2 \times F_c \times M_3 \times M^{-1}_3 \times R_t
= M^{-1}_2 \times F_c \times R_t
= M^{-1}_2 \times B_r.t.
\]  

(5)

In equation 5, $C_f$ is an $(n+1) \times (n+1)$ matrix and $C_f$ is
an $(n+1)$-dimensional vector which are both known to the
attacker. $B_r$ is an $(n+1)$-dimensional vector which can be
constructed by the attacker. $M^{-1}_2$ is one of the secret keys
which is an $(n+1) \times (n+1)$ matrix but unknown to the
attacker. Let $S$ be $C_f \times C_f$. To recover $M^{-1}_2$, the query
FingerCodes $\Gamma = [e_1b_1, e_2b_2, \cdots e_nb_n]$ which are extended to
$[\hat{B}^T_1, \hat{B}^T_2, \cdots \hat{B}^T_t]$ can be constructed, such that
\[
[S_1, S_2, \cdots S_t] = M^{-1}_2 \times [\hat{B}^T_1, \hat{B}^T_2, \cdots \hat{B}^T_t]
\]  

(6)

There are $(n+1) \times t$ known elements in $[S_1, S_2, \cdots S_t]$ and
$n(t+1)$ unknown elements in $[\hat{B}^T_1, \hat{B}^T_2, \cdots \hat{B}^T_t]$, $M^{-1}_2$ is a
matrix with $(n+1) \times (n+1)$ unknown elements.

Suppose $q$ to recover $M^{-1}_2$ by constructing special FingerCodes.

For the first row vector $q_1 = [q_{11}, q_{12}, \cdots q_{1(n+1)}]$ in $M^{-1}_2$, the
adversary constructs two special vectors as
$\hat{B}^T_1 = [1, 0, \cdots, -0.5]$ and $\hat{B}^T_2 = [2, 0, \cdots, -2]$. Then, the attacker
can compute as
\[
\begin{align*}
1 & \times q_{11} - 0.5 \times q_{1(n+1)} = S_{11} \\
2 & \times q_{11} - 2 \times q_{1(n+1)} = S_{21}.
\end{align*}
\]  

(7)

From equation 7, it is easy to compute $q_{11}$ and $q_{1(n+1)}$. Following the same analysis, the attacker can obtain all the
elements in $M^{-1}_2$ by constructing other special vectors.

After recovering $M^{-1}_2$, the attacker can compute the biometric data as follows:
\[
C_f \times C_f = H \times M_1^{-1} \times M_1 \times D_t \times M_2
= H \times D_t \times M_2
= B_r \times M_2.
\]  

(8)

In equation 8, $C_f$ and $C_i$ are known by the attacker. $M_2$ is
the secret key which is recovered by the above foregoing.
Therefore, the attacker can recover $B_r$.

IV. A NOVEL BIOMETRIC IDENTIFICATION SCHEME

In this section, we show the details of the proposed
biometric identification scheme.

A. OVERVIEW

We construct a novel biometric identification scheme to
address the weakness of Yuan and Yu’s scheme [13]. To achieve a higher level of privacy protection, a new retrieval
way is constructed to resist the level-3 attack. Moreover, we also
reconstruct the ciphertext to reduce the amount of uploaded data and improve the efficiency both in the
preparation and identification procedures.

In the remaining part of this section, we will introduce the
preparation process and the identification process.

B. PREPARATION PROCESS

In the preparation process, $b_i$ is the $i$-th sample feature
vector derived from the fingerprint image using a feature extraction algorithm [19]. To be more specific, $b_i$ is an $n$-
dimensional vector with $l$ bits of each element where $n = 640$ and $l = 8$.

For ease of identification, $b_i$ is extended by adding an $(n+1)$-th element as $B_i$. Then, the database owner encrypts $B_i$ with the secret key $M_1$ as follows:
\[
C_i = B_i \times M_1.
\]  

(9)
The database owner further performs the following operation:

\[ C_h = M_2^{-1} \times H^T. \]  \hspace{1cm} (10)

Each FingerCode \( B_i \) is associated with an index \( I_i \). After executing the encryption operations, the database owner uploads \( (C_i, C_{hi}, I_i) \) to the cloud.

**C. IDENTIFICATION PROCESS**

The identification process includes the following steps:

Step 1: When a user has a query fingerprint to be identified, he/she first gets the query FingerCode \( b \), derived from the query fingerprint image. The FingerCode \( b \) is also an \( n \)-dimensional vector. Then, the user sends \( b \) to the database owner.

Step 2: After receiving \( b \), the database owner extends \( b \) to \( B \) by adding the \( i \)-th row element equals to 1. Then the database owner randomly generates an \( (n + 1) \times (n + 1) \) matrix \( E \). The \( i \)-th row vector \( E_i = [E_{i1}, E_{i2}, \ldots, E_{in+1}] \) is set as a random vector, where the \( (n + 1) \)-th element is \( 1 - \sum_{j=1}^{n} E_{ij} \times H_j \) for \( 1 \leq i \leq (n + 1) \). After that, the database owner performs the following computation to hide \( B \):

\[ F_c = [E_1^T \times b_{c1}, E_2^T \times b_{c2}, \ldots, E_{(n+1)}^T \times b_{c(n+1)}]^T. \]  \hspace{1cm} (11)

To securely send \( F_c \) to the cloud, the database owner needs to encrypt \( F_c \) with the secret keys and a random integer \( r \). The computation is performed as follows:

\[ C_f = M_1^{-1} \times r \times F_c \times M_2 \]  \hspace{1cm} (12)

Then, the database owner sends \( C_f \) to the cloud for identification.

Step 3: After receiving \( C_f \) from the cloud, the cloud begins to search the FingerCode which has the minimum Euclidean distance with the query FingerCode \( B \). \( P_r \) denotes the relative distance between \( B \) and \( B \) as follows:

\[ P_r = C_i \times C_f \times C_h = B_i \times M_1 \times M_1^{-1} \times r \times F_c \times M_2 \times M_2^{-1} \times H^T = B_i \times r \times F_c \times H^T \]  \hspace{1cm} (13)

\[ = X_r \times b_{ij} \times b_{ij}. \]

Step 4: After receiving the index \( I_i \), the database owner gets the corresponding sample FingerCode \( b \) from the database \( D \) and calculates the accurate Euclidean distance between \( b \) and \( b_c \) as \( dist_{ic} = \sqrt{\sum_{j=1}^{n} (b_{ija} - b_{icj})^2} \). Then, the database owner compares the Euclidean distance with the standard threshold. If the distance is less than the threshold value, the query is identified. Otherwise, the identification fails.

Step 5: Finally, the database owner returns the identification result to the user.

**V. SECURITY ANALYSIS**

In this part, we first prove that our scheme is secure under level-2 and level-3 attacks, and then we will show the proposed scheme can resist the attack proposed by Zhu et al [18].

**A. SECURITY ANALYSIS UNDER LEVEL-2 ATTACK**

According to the attack scenario 2, an attacker can obtain some plaintexts of the biometric database, but does not know the corresponding ciphertexts.

We consider \( C_i \), which is obtained by multiplying \( B_i \) and \( M_1 \). Since the mapping relationship between \( B \) and \( C_i \) is not known, it is impossible for the attacker to compute \( B_i \) and \( M_1 \).
B. SECURITY ANALYSIS UNDER LEVEL-3 ATTACK

In the level-3 attack, besides the knowledge of encrypted data in the cloud, the attacker can forge a large number of query FingerCodes $\Gamma$ as inputs. In the following, we will show the proposed scheme is secure by proving that the secret keys cannot be recovered.

When colluding with the cloud, the attacker gets $C_j$ and $C_h$, and then performs the following operation:

$$C_j \times C_h = M_{1-1} \times r \times F_e \times M_2 \times M_{2-1} \times H_T$$

$$= M_{1-1} \times r \times F_e \times H_T$$

$$= M_{1-1} \times r \times B_e T.$$

In equation 15, since $r$ is a positive random integer in identification process, the attacker cannot compute the secret key $M_{1-1}$ directly.

Pretending a valid user, the attacker can construct $t$ query FingerCodes $\Gamma = [e b_1, e b_2, \cdots, e b_t]$ extended as $[B_{e_1}, B_{e_2}, \cdots, B_{e_t}]$ for identification, which introduces a set of positive random values $r_j$ and $C_{j}, 1 \leq j \leq t$. Let $P_{e}$ be the value of $C_{j} \times C_{h}$. The attacker computes $P_{e}$ as follows:

$$\widehat{P}_j = M_{1-1} \times r_j \times B_{e T} T_j .$$

After constructing $t$ equations, we have:

$$Pe = M_{1-1} T \times \cdots \times B_{e T} T \times \cdots \times (17) [B_{e1}, B_{e2}, \cdots, B_{et} T \times \cdots \times [0 \leq r_j \leq 0] .$$

$$M_{1-1} \times B_{e} \times R .$$

Here $[B_{e T} T, B_{e T} T, \cdots, B_{e T} T]$ is denoted as $R$, in this equation, $P_{e}$ is an $(n + 1) \times t$ matrix known to the attacker, $B_{e}$ is an $(n+1) \times t$ matrix constructed by the attacker, $R$ is an $(n+1) \times t$ matrix, since $r_j$ is a random positive integer, it is unknown to the attacker.

We then demonstrate that the attacker cannot recover $M_1$ according to Theorem 1.

Theorem 1. Assume after $t$ equations are constructed, $M_1$ cannot be computed in $P = M_{1-1} \times B \times R_{e} \times e$. When $(t + 1)$ equations are constructed, the following equation holds, and $M_1$ cannot be recovered.

$$\left[ \widehat{P} \right]_{t+1} = M_{1-1} \times B \times B_{T} T_{t+1} \times \left[ R_{e} \right]_{r_{t+1}} .$$

Proof. This theorem is proven with the inductive method. When $t = 1$, $M_1$ cannot be computed in equation 16. Assume the equation 17 holds, where $(t > 1)$. When $(t + 1)$ query FingerCodes are constructed, we obtain:

$$\left[ \widehat{P} \right]_{t+1} = M_{1-1} \times B \times B_{T} T_{t+1} \times \left[ R_{e} \right]_{r_{t+1}} .$$

(19) For $(t + 1)$-th query FingerCode $B_{e(t+1)}$, we have

$$\widehat{P}_{t+1} = M_{1-1} \times B_{T} T_{t+1} \times r_{t+1} .$$

From equation 20, we have

$$B_{T} T_{t+1} \times (M_{1-1})^T = (r_{t+1})^T \times \widehat{P}_{t+1} .$$

Let $(d_1, d_2, \cdots, d_{m_1})$ be the vector $(r_{t+1})^T \times \widehat{P}_{t+1}$, where

$$d_j = (r_{t+1})^T \times \widehat{P}_{t+1} .$$

Let $(M_{1-1})^T = (m_{1}, m_{2}, \cdots, m_{n+1})^T$, where $m_j$ denotes a row vector in $M_{1-1}$, $1 \leq j \leq (n + 1)$. The following equations hold:

$$B_{e(t+1)} \times (m_{1}, m_{2}, \cdots, m_{n+1}) = (d_1, d_2, \cdots, d_{m_1}) .$$

Equation 23 is a typical non-linear homogeneous equation. Since the rank of $B_{e(t+1)} = t(B_{e(t+1)})$, we assume the result is $\alpha \beta_1 + \alpha \beta_2 + \cdots + \alpha_{n-1} \beta_{n-1}$, $\beta_{n-1}$. We further state the special solution of equation 23 is $\beta'$ which satisfies the formula $B_{e(t+1)} \times m_{j} = d_{j}$. Because $d_j = (r_{t+1})^T \times \widehat{P}_{t+1}$, $d_j$ is included in the special solution $\beta'$. For $m_j$ in matrix $(M_{1-1})^T$, the particular solution of $m_j = \alpha \beta_1 + \alpha \beta_2 + \cdots + \alpha_{n-1} \beta_{n-1}$. Since $r$ is a random integer, the special solution $\beta'$ is uncertain as well, which means the attacker cannot derive the exact particular solution for $m_j$ in $(M_{1-1})^T$. Therefore, when $(t + 1)$ query FingerCodes are constructed, the secret key $M_1$ cannot be computed by the attacker as well.

As discussed above, the attacker cannot recover the secret key even if he is a malicious user. Therefore, the attacker cannot recover the biometric data as well.

Moreover, we compare our scheme with the schemes proposed in [13] and [14]. According to Table 1, other

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schemes have some weaknesses, while our scheme is secure under all the three level attacks.

| TABLE 1. Security comparison with other schemes. |  |
|----------------------------------------|---|---|---|
| Schemes | Level 1 attack | Level 2 attack | Level 3 attack |
| Yuan and Yu’s scheme [13] | Yes | Yes | No |
| Wang et al.’s scheme [14] | Yes | Yes | No |
| Our scheme | Yes | Yes | Yes |

\[ [P_{e1}, P_{e2}, \ldots, P_{en}] = [b_{i1}, b_{i2}, \ldots, b_{i(n+1)}] \times [r_1 B_{e1T}, r_2 B_{e2T}, \ldots, r_t B_{eT}] \]

C. SECURITY ANALYSIS UNDER THE ATTACK PROPOSED BY ZHU ET AL.

Zhu et al. [18] showed an attack for Yuan and Yu’s scheme. In their attack, the attacker observes the cloud and gets the values of relative distance. According to the equation 1, 2, 3, 4, the relative distance in Yuan and Yu’s scheme can be computed as follows:

\[ P_i = C_h \times C_1 \times C_j \times C_r \]
\[ = H \times M_{1-1} \times M_1 \times D_t \times M_2 \]
\[ \times M_{2-1} \times F_c \times M_3 \times M_{3-1} \times R_T \]
\[ = H \times D_t \times R_T \]
\[ = X b_{ij} \times b_{ij} \]
\[ = B_t \times B_{eT}. \]

As shown in equation 24, \( P_i \) is an integer which the attacker can get in the cloud. \( B_t \) is the extended query FingerCode which can be constructed by the attacker pretending to be a user. \( B_i \) is the extended sample FingerCode which is sensitive and should not be leaked. To recover \( B_t \), the attacker can construct \( t \) query FingerCodes \( r_i \) extended as \( [B_{e1}, B_{e2}, \ldots, B_{eT}] \) for identification. \( P_{eij} \) denotes the relative distance between the sample FingerCode \( B_i \) and the query FingerCode \( B_{ej} \) where \( 1 \leq j \leq t \). Then, the attacker has:

\[ [P_{e1}, P_{e2}, \ldots, P_{et}] = [b_{i1}, b_{i2}, \ldots, b_{i(n+1)}] \times [B_{e1T}, B_{e2T}, \ldots, B_{eT}] . \]

In this equation, \( P_{eij} \) and \( B_{ej} \) are known to the attacker. For each element in \( B_t \), it can be recovered if \( t \) equations are built, where \( t > (n+1) \).

Then, we demonstrate the proposed scheme is secure under the attack proposed by Zhu et al. In the proposed scheme, \( P_{eij} \) is set as the relative distance between \( B_i \) and \( B_{ej} \).

\[ P_{eij} = C_i \times C_j \times C_h \]
\[ = r_j \times B_i \times B_{eT}. \]

\( r_j \) is the \( j \)-th positive random integer in \( t \) identification processes. The attacker constructs \( t \) query FingerCodes and gets the equation as follows:

\[ [b_{i1}, b_{i2}, \ldots, b_{i(n+1)}] \times [B_{e1T}, B_{e2T}, \ldots, B_{eT}] \times [r_1 0 \ldots 0 0 \ldots r_t] \]

\[ = [b_{i1}, b_{i2}, \ldots, b_{i(n+1)}] \times [B_{e1T}, B_{e2T}, \ldots, B_{eT}] \times [r_1 0 \ldots 0 0 \ldots r_t]. \]

In this equation, \( r_j \) is a positive random integer which is unknown to the attacker. For every element in \( B_t \), after \( t \) computations, the attacker can only get the value of \( r_j \) and \( b_{ij} \) where \( t > (n+1), 1 \leq q \leq (n+1) \). For the reason that \( r_j \) is a random integer, \( r_j \times b_{ij} \) is also unexpected which means the attacker cannot acquire \( B_t \). Thus, the proposed scheme can resist the attack proposed by Zhu et al.

VI. PERFORMANCE ANALYSIS

To evaluate the performance of the proposed scheme, we implement a cloud-based privacy-preserving fingerprint identification system. For the cloud, we use 2 nodes with 6-core 2.10 GHz Intel Xeons CPU and 32GB memory. We utilize a laptop with an Intel Core 2.40 GHz CPU and 8G. Similar to [13] and [14], the query FingerCodes are
randomly selected from the database which is constructed with random 640entry vectors.

A. COMPLEXITY ANALYSIS

Table 2 summarizes the computation and communication costs on the data owner side, cloud server and users in our scheme and the schemes in [13] and [14]. In this work, each matrix multiplication costs $O(n^3)$, where $n$ denotes the dimension of a FingerCode, and the sorting cost of fuzzy Euclidean distances has time complexity of $O(m \log m)$. As illustrated in Table 2, our scheme has lower complexities in the preparation phase. That is, more computation and bandwidth costs can be saved for the database owner. In the identification phase, the computation complexity of our scheme is lower than that in [14]. The reason is that our scheme performs vector-matrix multiplication operations to find the close match, while [14] needs to execute matrix-matrix multiplication operations. Although the complexity of our scheme is the same as that in [13], we emphasize that [13] sacrifices the substantial security to achieve such fast computation of $P_i$. Moreover, our scheme executes fewer multiplication operations, and thus obtains better performance.

B. EXPERIMENTAL EVALUATION

Preparation phase. Fig. 2 and Fig. 3 show the computation and communication costs in the preparation phase with the number of FingerCodes varying from 1000 to 5000. As shown in Fig. 2, in our scheme, registering 5000 FingerCodes needs 29.37s, which can save about 88.85% and 90.58% time cost compared with [13] and [14] respectively. The reason is when encrypting a sample FingerCode, in our scheme, only one matrix is needed which leads to fewer matrix multiplication operations. Fig. 3 shows the bandwidth costs of the three schemes. Since the data outsourced to the cloud is in the form of vectors in comparison with matrices in the other two schemes, the communication cost in our scheme is much less than [13], [14].

Identification phase. Fig. 4 and Fig. 5 show the computation and communication costs in the identification phase with the number of FingerCodes ranges from 1000 to 5000. As demonstrated in Fig. 4, all schemes grow linearly as the size of database increases. As in our scheme fewer matrix multiplication operations are used than [13], it can save about 56% time cost. Compared with [14], the identification time can be saved as much as 84.75%, since the vector-matrix multiplication rather than the matrix-matrix multiplication operation is executed. The bandwidth costs of the three schemes, as shown in Fig. 5, are almost the same. The reason is that all schemes need to transmit a matrix in the identification phase.
VII. RELATED WORKS

Related works on privacy-preserving biometric identification are provided in this section. Recently, some efficient biometric identification schemes have been proposed. Wang and Hatzinakos proposed a privacy-preserving face recognition scheme [22]. Specifically, a face recognition method is designed by measuring the similarity between sorted index numbers vectors. Wong and Kim [23] proposed a privacy-preserving biometric matching protocol for iris codes verification. In their protocol, it is computationally infeasible for a malicious user to impersonate as an honest user. Barni et al. [10] presented a FingerCode identification protocol based on the Homomorphic Encryption technique. However, all distances are computed between the query and sample FingerCodes in the database, which introduces too much burden as the size of fingerprints increases. To improve the

TABLE 2. A summary of complexity costs. In the table, $m$ denotes the number of FingerCodes in the biometric database: $n \ll m$.

<table>
<thead>
<tr>
<th>Phases</th>
<th>Database owner</th>
<th>Cloud server</th>
<th>User</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preparation</td>
<td>$O(n^2)$</td>
<td>$O(mn^2 + m \log m)$</td>
<td>/</td>
</tr>
<tr>
<td>Identification</td>
<td>$O(n^2)$</td>
<td>$O(n^2)$</td>
<td>$O(n^2)$</td>
</tr>
<tr>
<td>Retrieval</td>
<td>$O(n)$</td>
<td>$O(n)$</td>
<td>$O(n)$</td>
</tr>
</tbody>
</table>

FIGURE 3. Bandwidth costs in the preparation phase.

FIGURE 4. Time costs in the identification phase.

FIGURE 5. Bandwidth costs in the identification phase.
efficiency, Evans et al. [12] proposed a novel protocol which reduces the identification time. They used an improved Homomorphic encryption algorithm to compute the Euclidean distance and designed novel garbled circuits to find the minimum distance. By exploiting a backtracking protocol, the best match FingerCode can be found. However, in [12], the whole encrypted database has to be transmitted to the user from the database server. Wong et al. [24] proposed an identification scheme based on kNN to achieve secure search in the encrypted database. However, their scheme assumes that there is no collusion between the client side and cloud server side. Yuan and Yu [13] proposed an efficient privacy-preserving biometric identification scheme. However, Zhu et al. [18] pointed out their protocol can be broken if a malicious user colludes with the cloud server in the identification process. Based on [13], Wang et al. presented a privacy-preserving biometric identification scheme in [14] which introduced random diagonal matrices, named CloudBI-II. However, their scheme has been proven insecure in [15], [16]. Recently, Zhang et al. [17] proposed an efficient privacy-preserving biometric identification scheme by using perturbed terms.

VIII. CONCLUSION
In this paper, we proposed a novel privacy-preserving biometric identification scheme in the cloud computing. To realize the efficiency and secure requirements, we have designed a new encryption algorithm and cloud authentication certification. The detailed analysis shows it can resist the potential attacks. Besides, through performance evaluations, we further demonstrated the proposed scheme meets the efficiency need well.

REFERENCES