Achieving Practical Symmetric Searchable Encryption With Search Pattern Privacy Over Cloud

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Abstract—Dynamic symmetric searchable encryption (SSE), which enables a data user to securely search and dynamically update the encrypted documents stored in a semi-trusted cloud server, has received considerable attention in recent years. However, the search and update operations in many previously reported SSE schemes will bring some additional privacy leakages, e.g., search pattern privacy, forward privacy and backward privacy. To the best of our knowledge, none of the existing dynamic SSE schemes preserves the search pattern privacy, and many backward private SSE schemes still leak some critical information, e.g., the identifiers containing a specific keyword currently in the database. Therefore, aiming at the above challenges, in this article, we design a practical SSE scheme, which not only supports the search pattern privacy but also enhances the backward privacy. Specifically, we first leverage the $k$-anonymity and encryption to design an obfuscating technique. Then, based on the obfuscating technique, pseudorandom function and pseudorandom generator, we design a basic dynamic SSE scheme to support single keyword queries and simultaneously achieve search pattern privacy and enhanced backward privacy. Furthermore, we also extend our proposed scheme to support more efficient boolean queries. Security analysis demonstrates that our proposed scheme can achieve the desired privacy properties, and the extensive performance evaluations also show that our proposed scheme is indeed efficient in terms of communication overhead and computational cost.

Index Terms—Dynamic SSE, search pattern privacy, enhanced backward privacy, boolean query

1 INTRODUCTION

As the data generated by the Internet of Things (IoT), social media and the web continue to increase, the global big data market will grow from $18.3bn in 2014 to an incredible $92.2bn by 2026 [1]. Such an explosive growth of data motivates an increasing number of individuals and organizations to outsource data to the powerful cloud [2], [3]. Meanwhile, as the data in some fields (e.g., eHealthcare) contain some private information and at the same time the cloud servers may not be fully trusted, data should be encrypted before being outsourced to the cloud. However, directly outsourcing encrypted data inevitably hides the characteristics of the data such as the keywords in the documents, and thus makes it challenging for the data user to search the outsourced documents meeting some criteria (e.g., “return all documents containing keyword $w$”). Although the data user can download each encrypted document and check whether it satisfies the search criteria or not, this approach is inefficient and impractical in terms of computational cost and communication overhead.

In order to achieve much more efficient search over outsourced encrypted documents, Song et al. [4] proposed the first searchable encryption scheme. After that, Goldwasser et al. [5] and Garg et al. [6] respectively introduced the fully homomorphic encryption and ORAM based searchable encryption schemes. Although both of the two schemes can achieve highly secure searchable encryption, the huge computational cost in the ORAM technique and fully homomorphic encryption technique makes the search efficiency in such schemes not desirable. Then, in order to balance the security and search efficiency of the searchable encryption schemes, symmetric searchable encryption (SSE) was proposed, which improves the search efficiency at the cost of small leakage including access pattern and search pattern. The access pattern reveals which documents are returned in a query and the search pattern leaks which search queries refer to the same keyword. After the first SSE was proposed in [4], Curtmola et al. [7] defined the security model of SSE, i.e., adaptive security of SSE, and introduced the first inverted index based SSE scheme. The inverted index technique builds a map from each keyword to the documents’ identifiers matching it, which is an important basis for many subsequent works including our work in this paper.

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Although the aforementioned proposals can support efficient search over encrypted data, most of them are static SSE and thus they cannot support the dynamic update of the outsourced encrypted data. Aiming at the dynamic update, Kamara et al. [8] introduced the first dynamic SSE scheme with sub-linear search time and followed by several other dynamic SSE schemes [9], [10]. However, due to the update operations, the dynamic SSE schemes have more potential leakages than the static SSE schemes. In specific, the addition operation may reveal the information regarding whether the current updated keyword was searched in previous queries, i.e., forward privacy. Similarly, the current search query may reveal the documents that match the current search keyword but have been deleted before, i.e., backward privacy.

Forward privacy was first introduced in [11] and it became increasingly important since Zhang et al. presented a file-injection attack in [12]. Such an attack is particularly effective, especially when the dynamic SSE schemes are not forward private [12]. However, as pointed out in [12], it is difficult to conduct the attack in the “closed systems”, as all documents in the “closed systems” are outsourced by the client and it is almost impossible for an adversary to inject documents into the systems. As for the backward privacy, it was first formally defined by Bost et al. [13]. In specific, they defined three types of backward privacy, i.e., type-I, type-II, and type-III backward privacy. Among them, the type-I backward privacy is the most secure one, and for a specific keyword \( w \), it only leaks the number of previous updates associated with \( w \), the identifiers containing \( w \) currently in the database, and when each of such documents was inserted. At the same time, Bost et al. and Chamani et al. respectively constructed a type-I backward private SSE scheme in [13] and [14].

Nevertheless, two challenges in the dynamic SSE schemes still have not been well addressed. The first one is that none of the existing dynamic SSE schemes preserves the search pattern privacy in an efficient way. Though ORAM or fully homomorphic encryption based searchable encryption schemes can achieve search pattern privacy, both of them are inefficient and impractical in terms of communication overhead and computational cost. The second one is that the current backward private SSE schemes still leak some critical information as mentioned above even if they have achieved type-I backward privacy. Thus, aiming at the above challenges, in this paper, we design a practical SSE scheme with search pattern privacy, forward privacy and enhanced backward privacy. Besides these privacy properties, our proposed scheme can be easily extended to support efficient boolean queries. Specifically, our contributions are four-fold as follows.

- First, we leverage \( k \)-anonymity technique and encryption technique to design an obfuscating technique, which serves as the core idea of our proposed scheme for privacy preservation.
- Second, based on the obfuscating technique, pseudorandom function and pseudorandom generator, we design a basic dynamic SSE scheme to support single keyword queries and achieve search pattern privacy, forward privacy and enhanced backward privacy, where the enhanced backward privacy leaks much less information than type-I backward privacy.
- Third, based on our basic scheme, we propose an extended SSE scheme supporting efficient boolean queries.
- Finally, we analyze the security of our proposed scheme and show that it achieves desired privacy properties. And at the same time, we conduct extensive experiments to evaluate its performance, and the results show that it is indeed efficient in terms of communication overhead and computational cost.

The remainder of this paper is organized as follows. In Section 2, we introduce our system model, security model and design goal. Then, we describe some preliminaries in Section 3. In Section 4, we present our scheme, followed by security analysis and performance evaluation in Sections 5 and 6, respectively. Finally, we describe the related work in Section 7 and draw our conclusion in Section 8.

2 MODELS AND DESIGN GOAL

In this section, we formalize our system model, security model, and identify our design goal.

2.1 System Model

In our system model, we consider a typical dynamic SSE scheme with support for both single keyword queries and boolean queries, which consists of two entities, i.e., one client and one (cloud) server, as shown in Fig. 1.

- Client: The client collects \( N \) documents with identifiers \( \mathbb{ID} = \{id_1, id_2, \ldots, id_N\} \). Each document \( id \) contains a set of keywords \( W \), which is a subset of the collection of all keywords \( W = \{w_1, w_2, \ldots, w_l\} \), i.e., \( W_i \subseteq W \). Due to the limited computational capability and storage space, the client stores his/her documents in the cloud server. As these documents may contain some sensitive information and the cloud server is not fully trusted, the client tends to encrypt them before outsourcing them to the server. Then, the client can access these documents by performing single keyword queries or boolean queries, e.g., a single keyword query may be “return all documents that contain keyword \( w_i \)”, and a boolean query may be a conjunctive query like “return documents that simultaneously contain a set of keywords, e.g., \( \{w_1, w_2\} \)”.

A straightforward method to deal with keyword queries is to traverse all encrypted documents and return documents that meet the queried criteria. However, the overhead of this method is too large. In order to improve the query efficiency, in this paper, the client builds an inverted index database DB for his/her keywords. As shown in Fig. 2, each data record in the index database DB corresponds to a keyword \( w_i \in W \) and a collection of documents’ identifiers containing \( w_i \), denoted by \( \mathbb{ID}_i \). After that, the client will encrypt DB and outsource it to the cloud server. With this index database, the client can efficiently access and maintain the documents in the cloud server. At the same time, both the
encrypted documents and the inverted index database can support users’ dynamic update, i.e., adding or deleting some keywords from a given document.

- Server: The (cloud) server is powerful in both computational capability and storage space. It is responsible for storing encrypted documents along with encrypted inverted index database outsourced by the client, and processing the keyword query requests from the client. In specific, on receiving a keyword query request, the cloud server finds out all documents’ identifiers satisfying the queried criteria and returns them to the client.

### 2.2 Security Model

In the security model of our dynamic SSE scheme, we consider the client is honest, i.e., he/she will follow the protocol sincerely. At the same time, the cloud server is considered to be honest-but-curious. That is, the cloud server will honestly follow the protocol to store the encrypted documents together with the inverted index database and deal with the keyword query requests from the client, while it may be curious about some private information, such as the plaintexts of documents and inverted index database stored in the server, as well as the queried keywords in the query requests. Besides, our system is designed to be a “closed system” and each data record must be encrypted by the client with the secret key, so the cloud server cannot launch the file-injection attack of [12] due to the difficulty of injecting attack documents. Besides the above security requirements, we aim to preserve three types of privacy in our dynamic SSE scheme, i.e., search pattern privacy, forward privacy and enhanced backward privacy. The details on these three types of privacy will be described in Section 3. Note that there may be other active attacks such as data pollution attack and denial of service attack, however, as we focus on privacy preservation in this work, those attacks are beyond the scope of this paper, and will be discussed in our future work.

### 2.3 Design Goal

In this work, our goal is to design a practical and privacy-preserving dynamic SSE scheme. Specifically, the following objectives should be satisfied.

- **Privacy preservation:** The basic security requirement of our proposed scheme is privacy preservation. That is, the data stored in the cloud server including encrypted documents and encrypted inverted index database should be privacy-preserving, and the queried keywords in the query requests should be privacy-preserving. At the same time, the proposed scheme should satisfy search pattern privacy, forward privacy and enhanced backward privacy, as described in Section 2.2.

- **Efficiency:** In order to achieve the above privacy requirement, additional communication overhead and computational cost will be incurred. Specifically, keyword search queries over encrypted inverted index database will increase the computational overhead at both the client side and the server side, and bring additional communication overhead between the client and the server. Thus, in the proposed scheme, we aim to minimize the communication overhead and computational cost during the keyword search queries.

### 3 PRELIMINARIES

In this section, we first introduce the formal definition and privacy concerns of dynamic SSE schemes. Then, we briefly review the pseudorandom function and pseudorandom generator techniques, which will be used in our proposed scheme.

#### 3.1 Dynamic SSE

A dynamic SSE scheme $\Sigma = (\text{Setup}, \text{Search}, \text{Update})$ is run between the client and the server, and consists of one algorithm $\text{Setup}$ and two protocols $\text{Search}$ and $\text{Update}$.

- **Setup($\lambda$):** Given a security parameter $\lambda$, the setup algorithm generates a secret key $K$ for the client and an encrypted index database $\text{EDB}$ for the cloud server. At the same time, it outputs the local state of the client $\sigma$.

- **Search($K, \sigma, w; \text{EDB}$):** The search protocol is used for performing keyword queries over the database and is run between the client and the server. In this protocol, the client and the server respectively inputs $(K, \sigma, w)$ and $\text{EDB}$, which denotes that the client intends to search all documents that contain keyword $w$ over EDB. As the output, the server protocol returns the collection of documents’ identifiers containing $w$, i.e., $\mathbb{I}_d$, to the client.

- **Update($K, \sigma, \text{id}, w, \text{op; EDB}$):** The update protocol, run between the client and the server, is used to update the database $\text{EDB}$. In this protocol, the client inputs $(K, \sigma, \text{id}, w, \text{op})$ to update a keyword $w$ in the document $\text{id}$, and the update operation $\text{op}$ is either addition or deletion.

#### Correctness:
Generally speaking, a dynamic SSE scheme is correct if and only if all search queries can return correct query results, e.g., the search query for $w_i$ can return exact $\mathbb{I}_d$. As for the formal definition of the correctness of the dynamic SSE scheme, we refer readers to [10] for details.

- **Security:** As described in [13], the security of the dynamic SSE scheme is measured by a leakage function $\mathcal{L} = (\mathcal{L}^\text{Setup}, \mathcal{L}^\text{Search}, \mathcal{L}^\text{Update})$, where $\mathcal{L}^\text{Setup}, \mathcal{L}^\text{Search}$ and $\mathcal{L}^\text{Update}$ are leakages with respect to the setup algorithm, search protocol and update protocol. Informally, a dynamic SSE scheme is secure if and only if it reveals nothing to the adversarial server except for the leakage function $\mathcal{L}$. This is formally captured by a real-world and ideal-world experiment defined as follows.

#### Definition 1 (Adaptive Security of Dynamic SSE [13]):

A dynamic SSE scheme $\Sigma = (\text{Setup}, \text{Search}, \text{Update})$ is adaptively secure with respect to the leakage function $\mathcal{L}$ iff for all PPT adversaries $\text{Adv}$ issuing polynomial number of queries $q$, there exists a PPT simulator $\text{Sim}$ such that $|\text{Pr}[\text{Real}^\Sigma_{\text{Adv}} (\lambda, q) = 1] - \text{Pr}[\text{Ideal}^\Sigma_{\text{Adv,Sim},\mathcal{L}} (\lambda, q) = 1]|$ is negligible in $\lambda$. 

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**Fig. 2.** Inverted index database building.
where $\text{Real}_{\text{Adv}}^{2}(\lambda, q)$ and $\text{Ideal}_{\text{Adv;Sim,E}}^{2}(\lambda, q)$ are two games defined as follows.

- $\text{Real}_{\text{Adv}}^{2}(\lambda, q)$: In the real-world game, the adversary Adv first gets back an index database $\text{EDB}$ generated by running the Setup($\lambda$) algorithm. Then, Adv can search/update the database $q$ times by calling the search/update protocol, where $q$ is a polynomial number. At the same time, Adv observes the real transcripts generated in the search/update protocol and outputs a bit $b$.

- $\text{Ideal}_{\text{Adv;Sim,E}}^{2}(\lambda, q)$: In the ideal-world game, the adversary Adv obtains an EDB generated by a simulator $\text{Sim}$ with leakage $L$. Then, Adv performs the same $q$ search/update operations as that in the real-world game by calling the simulator’s search/update protocol, where $q$ is a polynomial number. At the same time, Adv observes the simulated transcripts generated in the search/update protocol and outputs a bit $b$.

### 3.2 Privacy Concerns of Dynamic SSE

In dynamic SSE, search pattern captures the information that which queries refer to the same keyword and it is a common leakage in the existing dynamic SSE schemes [13], [14], [15]. Let $\text{QList}$ be a list of search queries and each query in $\text{QList}$ is in the form of $(t, w)$, which denotes that the keyword $w \in W$ is searched in timestamp $t$. Then, as described in [15], the search pattern over keyword $w$ can be defined as $sp(w) = \{t|(t, w) \in \text{QList}\}$.

**Definition 2 (Search Pattern Privacy).** An $L$-adaptively secure SSE scheme keeps search pattern privacy iff $L^{\text{Search}}$ does not leak the search pattern information, i.e., $\{sp(w)|w \in W\}$.

Forward privacy of dynamic SSE schemes was first proposed in [11] and attracted great attention after the file-injection attack was proposed [12]. Generally speaking, the forward privacy guarantees that the keyword related to the current update operation should not be linked to keywords that were searched before. Suppose that $\text{LastTime}(w)$ leaks the timestamp when $w$ was last searched/updated. At the same time, $\text{LastTime}(W) = \{\text{LastTime}(w_1), \ldots, \text{LastTime}(w_d)\}$ leaks the last updated/searched timestamp of each $w \in W$, but the one-to-one relationship between $\text{LastTime}(w)$ and $w$ is hidden. In other words, with $\text{LastTime}(W)$, it is difficult for the adversary to distinguish which one is the latest searched/updated timestamp of a specific keyword $w$. Then, the forward privacy can be formally defined as follows.

**Definition 3 (Forward Privacy).** An $L$-adaptively secure SSE scheme keeps forward privacy iff the update leakage function $L^{\text{Update}}$ can be written as: $L^{\text{Update}}(op, w, id_j) = L^{s}(op, id_j, \text{LastTime}(W))$, where $op$ is addition or deletion and $L^{s}$ is a stateless function.

Backward privacy of dynamic SSE ensures that search queries on keyword $w_i$ cannot be linked to the documents that contain $w_i$ but have been deleted previously. Bost et al. first formally defined the backward privacy and introduced three types of backward privacy with different leakage functions in [13], where the type-I backward privacy leaks the least information. In specific, it leaks the number and type of previous updates matching each keyword $w_i$, the documents’ identifiers matching $w_i$ in the current database, and when each such document was inserted [13]. In this work, we aim to further reduce the leakage of backward privacy and achieve enhanced backward privacy with less leakage than the type-I backward privacy. Specifically, the enhanced backward privacy only leaks each update operation, updated document’s identifier, the documents’ identifiers matching the searched keyword and $\text{LastTime}(W)$. However, different from the leakages defined in the type-I backward privacy, the leakages in the enhanced backward privacy cannot be matched to a specific keyword, which makes these leakages become trivial for adversary. Thus, the enhanced backward privacy leaks less information than the type-I backward privacy and can be formally defined as follows.

**Definition 4 (Enhanced Backward Privacy).** An $L$-adaptively secure SSE scheme keeps the enhanced backward privacy iff the leakage function $L$ satisfies that $L^{\text{Update}}(op, w, id_j) = L^{s}(op, id_j, \text{LastTime}(W))$, and $L^{\text{Search}}(w) = L^{s}(\mathbb{ID}_i, \text{LastTime}(W))$, where $L^{s}$ and $L^{s'}$ are two stateless functions, and $\mathbb{ID}_i$ contains the documents’ identifiers matching $w_i$.

### 3.3 Pseudorandom Function

The pseudorandom function (PRF) is a kind of random encryption function, which was first proposed by Goldreich et al. [16]. Let $F: \mathcal{K} \times \mathcal{X} \rightarrow \mathcal{Y}$ denote a PRF family from $\mathcal{X}$ to $\mathcal{Y}$, where $\mathcal{K}$ denotes the key space $\{0, 1\}^\lambda$. Then, without knowing the secret key $K$, it is difficult to distinguish $F(K \cdot x)$ from $F'(K \cdot x)$, where $K$ is randomly chosen from $\mathcal{K}$ and $F'$ is a random function from $\mathcal{X} \rightarrow \mathcal{Y}$. That is, for all PPT adversaries Adv, $\Pr[\text{Adv}(F(K \cdot); 1) = 1] - \Pr[\text{Adv}(F'(K \cdot); 1) = 1]$ is negligible in $\lambda$.

### 3.4 Pseudorandom Generator

Let $G: \mathcal{X} \rightarrow \mathcal{Y}$ denote a pseudorandom generator (PRG). Given a seed $x \in \mathcal{X}$, $G$ can generate a long random number $G(x) \in \mathcal{Y}$. At the same time, for all PPT adversaries Adv, it is difficult to distinguish $G(x)$ from a random number $x'$, i.e., $\Pr[\text{Adv}(G(x)) = 1] - \Pr[\text{Adv}(x') = 1]$ is negligible, where $x'$ has the same length with $G(x)$.

### 4 Our Proposed Scheme

In this section, we present a basic SSE scheme supporting single keyword queries. Then, based on the basic SSE scheme, we propose an extended SSE scheme supporting boolean queries. Before delving into the details, we first introduce an obfuscating technique, which serves as the core idea of both our basic SSE scheme and the extended one.

#### 4.1 The Obfuscating Technique

Suppose that the encrypted index database (i.e., EDB) is stored as a map in the server. Each data record in EDB is a key-value pair $(\text{loc}_i, c_i)$ associated with a specific $w_i$, where $c_i$ denotes the encrypted $\mathbb{ID}_i$ and $\text{loc}_i$ denotes $c_i$’s location in EDB. Then, we can design an obfuscating technique to access EDB with search pattern privacy. The main idea is to access the data record with $k$-anonymity technique, and re-encrypt the accessed data record with a new key-value pair.
In specific, when the client intends to access a data record associated with a specific keyword \( w_i \), he/she will simultaneously access \( k \) data records matching \( w_i \) and other \( k-1 \) random keywords. Suppose that \( \{(loc_1, c_1), \ldots, (loc_k, c_k)\} \) denotes the key-value pairs of the \( k \) accessed data records in EDB. Then, after the client accesses these data records, he/she will generate \( k \) new key-value pairs \( \{(loc'_1, c'_1), \ldots, (loc'_k, c'_k)\} \) and restore them to EDB. These key-value pairs satisfy the obfuscation property. That is, without the secret key, the adversary has no idea on the one-to-one match between new key-value pairs \( \{(loc'_1, c'_1), \ldots, (loc'_k, c'_k)\} \) and original key-value pairs \( \{(loc_1, c_1), \ldots, (loc_k, c_k)\} \). Fig. 3 is an example of the obfuscating technique when \( k = 3 \). From Fig. 3, we can see that original key-value pairs \( \{(loc_1, c_1), (loc_2, c_2), (loc_3, c_3)\} \) and new key-value pairs \( \{(loc'_1, c'_1), (loc'_2, c'_2), (loc'_3, c'_3)\} \) look like they are randomly stored in EDB and the one-to-one match between them is hidden. In other words, the obfuscating technique preserves the privacy that which grey location \( (loc_1, c_1) \) is stored and which black location \( (loc'_1, c'_1) \) is stored.

At the same time, the obfuscating technique preserves the privacy that which two locations including a grey location and a black location correspond to a same keyword \( w_i \) for \( i = 1, 2, 3 \). Furthermore, the obfuscating technique can well preserve the search pattern privacy and the details will be introduced in Section 5.

### 4.2 Basic SSE Scheme Supporting Single Keyword Queries

Based on the obfuscating technique, we present our basic SSE scheme supporting single keyword queries, which is comprised of one algorithm **Setup**, as well as two protocols **Search** and **Update**.

#### 4.2.1 Setup

The client is responsible for bootstrapping the scheme by running the setup algorithm, as shown in Algorithm 1. In specific, given a security parameter \( \lambda \), the client first generates a secret key \( K \) for the pseudorandom function \( F \). Then, he/she initializes two empty maps **FileCnt** and **DictW**, which respectively store the total number of times that each keyword is accessed and the encrypted index database EDB. In the setup phase, each keyword’s value in **FileCnt** is set to be 0, i.e., \( \{\text{FileCnt}[w_i] = 0 | w_i \in \mathbb{W}\} \). At the same time, for each data record \( (w_i, ID_i) \in \text{EDB} \), the client first represents \( ID_i \) to be an \( N \)-bit bitmap \( B_{i,j} = b_{i,j,1} \cdot b_{i,j,2} \cdots \cdot b_{i,j,N} \), where \( N \) is set to be the maximum number of documents in the system and each bit \( b_{i,j} \) is associated with the document \( id_j \) for \( j = 1, 2, \ldots, N \). If \( id_j \) belongs to \( ID_i \), \( b_{i,j} \) is set to be 1. Otherwise, \( b_{i,j} = 0 \). Then, the client encrypts \( (w_i, B_i) \) as \( c_i = G(F_K(w_i, \text{FileCnt}[w_i][1]) \oplus B_i \) and places it in **DictW** at the location of \( loc_i = F_K(w_i, \text{FileCnt}[w_i][0]) \), i.e., **DictW**[\( loc_i \)] = \( c_i \), where \( G \) is a pseudorandom generator and generates \( N \) binary bits. Note that, \( ID_i \) is empty in the setup phase, so each bit \( b_{i,j} \) in bitmap \( B_{i,j} = b_{i,j,1} \cdot b_{i,j,2} \cdots \cdot b_{i,j,N} \) is set to be 0, i.e., \( b_{i,j} = 0 \) for \( j = 1, 2, \ldots, N \). Finally, the client sends **DictW** to the server and locally keeps \( K \) and **FileCnt**, where **DictW** and **FileCnt** are respectively regarded as the encrypted index database EDB and the client’s local state \( \sigma \).

#### Algorithm 1. **Setup**(\( \lambda \))

1: \( K \leftarrow \text{Gen}(\lambda^2) \)
2: **FileCnt**, **DictW** \( \leftarrow \) empty map
3: for \( i = 1 \) to \( d \) do
4: **FileCnt**[\( w_i \)] = 0
5: Bits \( B_i = b_{i,1}b_{i,2} \ldots \cdot b_{i,N} = 0 \ldots 0 \)
6: loc\( _i = F_K(w_i, \text{FileCnt}[w_i][0]) \)
7: \( c_i = G(F_K(w_i, \text{FileCnt}[w_i][1]) \oplus B_i \)
8: **DictW**[\( loc_i \)] = \( c_i \)
9: end for
10: \( \sigma \leftarrow \text{FileCnt} \)
11: EDB \( \leftarrow \text{DictW} \)
12: return EDB to the server

#### 4.2.2 Search

As shown in Algorithm 2, the client can search the documents containing a specific keyword \( w_i \) as the following steps.

- **Step-1:** Given a search keyword \( w_i \), the client randomly chooses \( k - 1 \) distinct keywords from \( \mathbb{W}\setminus\{w_i\} \). In this case, counting the queried keyword \( w_i \), the client has \( k \) keywords in total, denoted by \( w_{r,1,}, w_{r,2}, \ldots, w_{r,k} \). For each keyword \( w_{r,i} \), the client computes its location in EDB as \( loc_i = F_K(w_{r,i}, \text{FileCnt}[w_{r,i}][0]) \) for \( i = 1, 2, \ldots, k \). Then, the client sends these \( k \) locations \( \{loc_1, loc_2, \ldots, loc_k\} \) to the server.

- **Step-2:** On receiving locations \( \{loc_1, loc_2, \ldots, loc_k\} \) from the client, the server finds out the encrypted value of each location in **DictW**, i.e., **DictW**[\( loc_i \)] for \( i = 1, 2, \ldots, k \), and puts them in CList. Then, it returns CList to the client.

- **Step-3:** On receiving the CList containing \( k \) encrypted values from the server, the client uses secret key \( K \) to recover each \( B_{r,i} \) as \( B_{r,i} = \text{CList}[\|l \| \oplus G(F_K(w_{r,i}, \text{FileCnt}[w_{r,i}][1])) \) for \( i = 1, 2, \ldots, k \). If \( r \) is equal to \( i \), the client recovers \( ID_i \) from \( B_{r,i} \) (i.e., \( B_i \)) to obtain all documents’ identifiers matching \( w_i \), i.e., the desirable query result.

- **Step-4:** The client updates each \( w_i \)'s value in **FileCnt**, i.e., **FileCnt**[\( w_i \)] = **FileCnt**[\( w_i \)] + 1. Then, with the
updated $FileCnt[w_i]$, the client generates a new key-value pair $(loc_i, q_i)$ for $(w_i, B_i)$, where $loc_i = F_K(w_i, FileCnt[w_i]|0)$ and $q_i = G(F_K(w_i, FileCnt[w_i]|1)) \oplus B_i$. After that, the client sends these $k$ new key-value pairs to the server.

- **Step 5:** Finally, the server stores each new key-value pair in $DictW$, i.e., $\{DictW[loc] = c_i|l = 1, 2, \ldots, k\}$.

**Algorithm 2. Search($K, w_i, \sigma, k; EDB$)**

Client:
1. Randomly choose $k$ distinct keywords from $W \setminus \{w_i\}$
2. $w_i$ and the chosen keywords are denoted by $\{w_{i1}, \ldots, w_{ik}\}$
3. $LocList = \{\}$
4. for $l = 1$ to $k$
5. $loc_i = F_K(w_{il}, FileCnt[w_{il}]|0)$
6. $LocList = LocList \cup loc_i$
7. end for
8. Send $LocList = \{loc_{i1}, \ldots, loc_{ik}\}$ to the server

Server:
9. $CList = \{\}$
10. for $l = 1$ to $LocList.size$
11. $B_i = CList[l] \oplus G(F_K(w_{il}, FileCnt[w_{il}]|1)$
12. if $r_i == i$
13. Recover $\mathbb{D}_l$ from $B_i$ ($B_j$), i.e., the desirable result
14. end if
15. end for
16. // Generate new key-value pairs
17. LocList = $\{\}$, $CList = \{\}$
18. for $l = 1$ to $k$
19. $FileCnt[w_{il}]++$
20. $loc_i = F_K(w_{il}, FileCnt[w_{il}]|0)$
21. $q_i = G(F_K(w_{il}, FileCnt[w_{il}]|1)) \oplus B_i$
22. $LocList = LocList \cup loc_i$
23. $CList = CList \cup q_i$
24. end for
25. Send LocList and $CList$ to the server

4.2.3 Update

The update protocol is designed for updating the documents stored on the server, where the update operations include addition and deletion. That is, the client can add/delete a keyword $w_i$ from a given document $id_j$ as follows.

The first two steps in the update protocol are the same as that in the search protocol, so the client and the server first run the first two steps of the search protocol, which returns $CList$ to the client. Then, the client uses the secret key $K$ to recover each $B_i$ as $B_i = CList[l] \oplus G(F_K(w_{il}, FileCnt[w_{il}]|1)$ for $l = 1, 2, \ldots, k$. After that, based on the update operation $op$, the client adds/deletes $w_i$ from $id_j$ by updating $w_i$’s bitmap $B_i$ ($B_j$). If $op$ is addition, set $b_{ij} = 1$. Otherwise, $b_{ij} = 0$. Finally, the client and the server follow step 4 and step 5 of the search protocol to finish the remaining update protocol. That is, the client generates a new key-value pair for each $(w_i, B_i)$ and sends them to the server. On receiving new key-value pairs from the client, the server stores them in EDB.

**Algorithm 3. Update($K, op, (w_i, id_j), \sigma, k; EDB$)**

1. The client and the server run the first two steps of the search protocol, which returns $CList$ to the client.
2. for $l = 1$ to $CList.size$
3. $B_i = CList[l] \oplus G(F_K(w_{il}, FileCnt[w_{il}]|1)$
4. if $r_i == i$
5. if $op ==$ addition then
6. set $b_{ij} = 1$ in $B_i = b_{i1}b_{i2}\ldots b_{iN}$
7. else if $op ==$ deletion then
8. set $b_{ij} = 0$ in $B_i = b_{i1}b_{i2}\ldots b_{iN}$
9. end if
10. end if
11. end for
12. The client and the server follow step 4 and step 5 of the search protocol to finish the remaining update protocol.

Note that, in the update protocol, one update operation allows the client to update one keyword for a given document. Then, when the client intends to add/remove a document with $u$ keywords, the client needs to run the update protocol $u$ times in total, i.e., add/remove these $u$ keywords one by one. In addition, the anonymous parameter $k$ in the update protocol is closely related to the security level of our proposed scheme, i.e., the security is strengthened as $k$ becomes larger. At the same time, it can be dynamically changed among different search queries or update operations according to different security requirements.

4.3 Extended SSE Scheme Supporting Boolean Queries

In this subsection, we extend our basic SSE scheme to support boolean queries, i.e., search the documents whose keywords satisfy a specific boolean function $BF(w_{i1}, \ldots, w_{ik})$, where $\{w_{i1}, \ldots, w_{ik}\}$ is a set of queried keywords. In specific, the boolean function $BF(w_{i1}, \ldots, w_{ik})$ can support the “AND”, “OR” and “NOT” operations between keywords $\{w_{i1}, \ldots, w_{ik}\}$. When the client intends to do such kind of boolean queries, he/she first chooses an anonymous parameter $k$ such that $k$ is satisfied with the security requirement and $k > u$. With $k$, the client selects $(k - u)$ random keywords and uses them together with $u$ queried keywords to construct a search query. Then, he/she follows the search protocol to obtain a set of bitmaps $\{B_{i1}, \ldots, B_{ik}\}$ matching the queried keywords $\{w_{i1}, \ldots, w_{ik}\}$. With these bitmaps, the client computes the boolean function $BF(B_{i1}, \ldots, B_{ik})$ and the result is the bitmap of the documents’ identifiers satisfying $BF(w_{i1}, \ldots, w_{ik})$. For example, when $BF(w_{i1}, w_{i2}, w_{i3}) = w_{i1} \land w_{i2} \land w_{i3}$ and the bitmaps matching $\{w_{i1}, w_{i2}, w_{i3}\}$ are $\{B_{i1}, B_{i2}, B_{i3}\}$, the client can compute $BF(B_{i1}, B_{i2}, B_{i3}) = B_{i1} \land B_{i2} \land B_{i3}$, which is the bitmap of documents’ identifiers satisfying $w_{i1} \land w_{i2} \land w_{i3}$. Furthermore, the client recovers the documents’ identifiers from the bitmap $B_{i1} \land B_{i2} \land B_{i3}$. At the same time, he/she follows the search protocol to generate $k$ new key-value pairs for the $k$ searched keywords and sends them back to the server. Since the overall procedure of the
boolean queries is the same as that of single keyword queries, the boolean queries in our extended SSE scheme are as efficient as single keyword queries in our basic SSE scheme.

Discussion. Note that both our basic scheme and extended scheme can support multiple-keyword update, i.e., the client can update and delete multiple keywords together. In specific, if the client attempts to update $u$ keywords \( \{w_{q_1}, \ldots, w_{q_u}\} \), he/she first chooses an anonymous parameter $k$ such that $k$ is satisfied with the security requirement and $k > u$. With $k$, the client selects $(k-u)$ random keywords and uses them together with $u$ query keywords to construct update request. Then, he/she follows the update protocol to obtain a set of bitmaps \( \{B_{q_1}, \ldots, B_{q_u}\} \) matching the updated keywords \( \{w_{q_1}, \ldots, w_{q_u}\} \). Finally, the client updates these bitmaps, generates $k$ new key-value pairs for all $k$ keywords, and sends them back to the server. The multiple-keyword update operation allows the client to add a new document or remove an obsolete document much more efficiently than the single keyword update protocol in our basic scheme because a multi-keyword update operation can simultaneously update multiple keywords instead of one keyword.

5 Security Analysis

In this section, we analyze the security of our basic SSE scheme and extended SSE scheme. In specific, we present that our proposed scheme achieves the privacy concerns described in Section 3.2, i.e., search pattern privacy, forward privacy and enhanced backward privacy.

5.1 Security Analysis of Basic SSE Scheme

- Search Pattern Privacy: The search pattern is the information regarding which queries refer to the same queried keyword. Since the obfuscating technique employs the $k$-anonymous query technique, which processes the queried keyword together with $k-1$ random keywords, it is difficult for the adversary to distinguish which keyword is the real queried keyword. Then, if the adversary attempts to link all queries matching a specific queried keyword $w_i \in \mathbb{W}$, the first step is to collect all queries containing $w_i$, and the second step is to distinguish in which queries $w_i$ is regarded as a random keyword and in which queries $w_i$ is a real queried keyword. In the first step, the adversary can use a backtracking method to track all possible queries involving the keyword $w_i$.

Suppose that a single keyword query $Q$ involves $k$ keywords including a real queried keyword $w_i$ and $k-1$ random keywords. At the same time, these keywords correspond to $k$ key-value pairs in EDB. Then, based on them, the adversary can backtrack $k$ previous search queries, called $Q$’s adjacent queries, in which the $k$ key-value pairs accessed in $Q$ are respectively updated. For example, if the query $Q$ accesses EDB’s encrypted values \( \{c_1, c_2, \ldots, c_k\} \), queries \( \{Q_1, Q_2, \ldots, Q_k\} \) are $Q$’s adjacent queries when $c_j$ is updated in $Q_j$, as shown in Fig. 4. Similarly, the adversary can continue to backtrack each $Q_j$’s adjacent queries and $Q_i$’s adjacent queries’ adjacent queries until no more queries can be further backtracked. Then, the backtracking process forms a backtracking tree with the query $Q$ as the root node, and only one path from $Q$ to the first query containing $w_i$ is the exact query sequence containing $w_i$. If the depth of the backtracking tree is $h$, the adversary has probability $\frac{1}{h}$ to successfully discover the correct queries sequence matching $w_i$. As shown in the Fig. 4, when $h = 2$ and the queries sequence matching $w_i$ is \( \{Q_{11} \rightarrow Q_1 \rightarrow Q\} \), the probability of linking them together is $\frac{1}{2}$. Then, when $k = 10$ and $h = 10$, the probability will be $1 \times 10^{-10}$. Thus, it is difficult for the adversary to discover all queries involving $w_i$. Even if he/she discovers all queries involving $w_i$, the client is still not confident with the result, since $w_i$ may be just a random keyword in some of such queries. Therefore, our basic SSE scheme can well preserve the search pattern privacy. In addition, the search pattern privacy also enables our basic scheme to resist the keyword frequency attack, i.e., the server uses the frequency of each keyword being queried to infer the queried keyword in a specific query.

- Forward Privacy: The forward privacy ensures that the current update keyword should not be linked to the keywords that were searched before. In our basic SSE scheme, the update protocol is $k$-anonymous, i.e., during an update operation, the updated keyword will be updated together with other $k-1$ random keywords. Suppose that $w_i$ is the updated keyword and \( \{w_{r_1}, w_{r_2}, \ldots, w_{r_{k-1}}\} \) denotes $k-1$ random keywords. Then, in the update protocol, the client sends an update request together with $k$ locations matching $w_i$ and other $k-1$ random keywords to the server, where these $k$ locations are generated by PRF. The security of PRF guarantees that the server can only observe $k$ locations and has no idea on real keywords matching these locations. Similarly, in the search protocol, the client also has no idea on which $k$ keywords are being searched. Then, it is difficult for the server to break the forward privacy by deducing the real keywords in the current update operation and previous search queries.

Without knowing the real keywords, the server just can observe the relationship of encrypted data records matching the updated/searched keywords to infer the relationship between the current keyword and previous searched
keywords. Given \( k \) encrypted data records in the current update operation, the server has \( \frac{1}{k} \) probability to successfully guess which one exactly matches the updated keyword \( w_i \). Then, the server can further find the current query’s adjacent update/search queries. The adjacent query is either an update query or a search query. In case of the update query, the server has to continue to find adjacent queries’ adjacent queries. However, it is more difficult for the server to match them with \( w_i \) because an adjacent query has \( k \) adjacent queries and each such query also contains \( k \) queried keyword. Even if the previous query is a search query, the adversary also cannot confirm whether \( w_i \) is regarded as a queried keyword or a random keyword in that query. At the same time, the latter case, i.e., \( w_i \) is just regarded as a random keyword, is more likely to appear under the assumption that each keyword is randomly searched. In this case, it is difficult for the server to link previous search queries matching \( w_i \) with the current update operation.

Besides, the update operation in our basic SSE scheme only leaks the type of update operation \( op \), the identifier of the updated document \( id_j \) and all keywords’ last updated timestamps \( LastTime(W_j) \), i.e., \( L^{\text{Update}}(op, w_i, id_j) = L^C(op, id_j, LastTime(W_j)) \). Actually, the leakage of \( op \) and \( id_j \) comes from the update on the real document. In specific, the real updated document and its length change respectively leak the identifier of updated document and the update operation. Thus, based on the definition of forward privacy, our basic SSE scheme can achieve forward privacy.

- **Enhanced Backward Privacy:** The enhanced backward privacy ensures that search queries on keyword \( w_i \) cannot be linked to the documents that contain \( w_i \) but have been deleted previously. The documents’ identifiers that contain \( w_i \) but have been deleted previously can be leaked in two ways. The first way is that \( ID \) contains such kind of identifiers, but it is almost impossible to happen in our basic SSE scheme. This is because the client will immediately change \( ID \) when a document deletes \( w_i \). Thus, \( ID \) cannot contain the documents’ identifiers that have been deleted. The second way is to link the current search query with previous deletion update queries, which is also difficult in practice. Since the search protocol and update protocol are extremely similar, and both of them conduct \( k \)-anonymous queries. Thus, linking an update query with previous search queries matching \( w_i \) is as difficult as linking a search query with previous update queries matching \( w_i \). In the above discussion, we have shown that it is difficult for the server to link an update query with previous search queries. Thus, it is difficult to link a search query with previous update queries. Furthermore, it is also difficult to link a search query with previous deletion update queries.

Besides, as discussed above, the leakage function of the update operation is \( L^{\text{Update}}(op, w_i, id_j) = L^C(op, id_j, LastTime(W_j)) \). At the same time, the search query leaks the documents’ identifiers matching each searched keyword and all keywords’ last updated timestamps, i.e., \( L^{\text{Search}}(w_i) = L^C(ID, LastTime(W_j)) \). Actually, the leakage \( ID \) comes from the search on real documents. For example, when the client recovers \( ID \), he/she needs to request the real documents by sending \( ID \) to the server, which will leak \( ID \) to the server. Thus, based on the definition of backward privacy, our basic SSE scheme satisfies enhanced backward privacy.

**Theorem 1.** Suppose that \( F \) and \( G \) are secure PRF and PRG, our basic SSE scheme is adaptively-secure with leakage \( L^{\text{Update}}(op, w_i, id_j) = L^C(op, id_j, LastTime(W_j)) \) and \( L^{\text{Search}}(w_i) = L^C(ID, LastTime(W_j)) \).

**Proof.** In the real-world game, suppose that the server observes \( q \) transcripts in total. The transcript observed from the setup algorithm includes the initialized EDB, and each other transcript observed from the update/search protocol includes \( k \) original key-value pairs and \( k \) updated key-value pairs matching the queried keywords as described in Section 4.2. In the following, we describe our simulator Sim, which is comprised of three algorithms, i.e., SimSetup, SimUpdate and SimSearch.

- **SimSetup(\( \lambda \)):** In the setup algorithm, Sim first generates \( d \) key-value pairs \( \{(loc_c, c_i) | i = 1, 2, \ldots, d\} \), where each \( loc_c \) is a random number in the range of \( F \) and each \( c_i \) is a random binary string with length \( N \). For each key-value pair \( (loc_c, c_i) \), Sim sets \( DictW[loc_c] = c_i \). Then, it sets EDB to be \( DictW \) and sends it to the server. Finally, Sim sets the local state of the simulator to be null, i.e., \( \sigma_G = \text{null} \), and locally stores each \( loc_c \) and the timestamp that it was last updated, i.e., \( \{(t, loc_c) | i = 1, 2, \ldots, d\} \).

- **SimUpdate(\( \sigma_G, L^{\text{Update}}(op, w_i, id_j), EDB) \):** In the update protocol, Sim receives the leakage function \( L^{\text{Update}}(op, w_i, id_j) = L^C(op, id_j, LastTime(W_j)) \). Suppose that the involved \( k \) key-value pairs matching the queried keywords were last updated in timestamps \( \{t_1, \ldots, t_k\} \), respectively. Then, Sim randomly chooses \( k \) locations \( \{loc_l, loc_2, \ldots, loc_k\} \) such that the last update timestamp of each \( loc_i \) is \( t_l \) for \( l = 1, 2, \ldots, k \), and sends them to the server. After receiving the response from the server, Sim randomly generates \( k \) new key-value pairs, where each location is a random number in the range of \( F \) and each value is a random binary string with length \( N \). Finally, Sim sends them to the server, and locally stores each location and the timestamp that it was last updated.

- **SimSearch(\( \sigma_G, L^{\text{Search}}(w_i), EDB) \):** In the search protocol, Sim receives the leakage function \( L^{\text{Search}}(w_i) = L^C(ID, LastTime(W_j)) \). Sim first chooses \( k \) random locations with the same method in the SimUpdate protocol and sends them to the server. When receiving the response from the server, Sim randomly generates \( k \) new key-value pairs and sends them to the server. At the same time, Sim locally stores each location and the timestamp that it was last updated. Finally, Sim sends \( ID \) to the server.

For the transcript in the setup algorithm, since the \( d \) key-value pairs in the real-world game are generated by the PRF \( F \) and PRG \( G \), they are indistinguishable from the random key-value pairs in the ideal-world game. For the transcripts in the update/search protocol, the timestamps of the \( k \) locations matching the queried keywords in the ideal-world game are the same as that in the real-world game, and the documents’ identifiers matching the searched/updated keyword \( w_i \) in the ideal-world game are the same as that in the real-world game. Thus, the transcripts of search/update protocol in the ideal-world game are also indistinguishable from those in the real-world game. Consequently, all the \( q \) transcripts in the ideal-world game are indistinguishable from those in the real-world game. Therefore, our basic SSE scheme is adaptively-secure with leakage \( L^{\text{Update}} \) and \( L^{\text{Search}} \).
5.2 Security Analysis of Extended SSE Scheme
For our extended SSE scheme, the forward privacy and enhanced backward privacy can be achieved and the detailed security analysis is the same as that in our basic SSE scheme. As for the search pattern privacy, it can be analyzed from two aspects. On the one hand, we consider the search pattern privacy of a single queried keyword, which is the same as that in the basic SSE scheme. Thus, the single keyword’s search pattern privacy can be easily achieved. On the other hand, we consider the search pattern privacy when regarding all involved keywords as a whole. In this case, the search pattern means the information that which queries refer to the same set of queried keywords. Since a boolean query contains multiple keywords and the number of possible keywords combinations in a search query is large, about \(2^d - \binom{d}{1} = 2^d - 1\) when at least one keyword is queried, where \(d\) is the number of keywords, the number of queries containing the same keywords set is relatively small. In specific, a single keyword query in the basic SSE scheme only contains a real queried keyword and has \(d\) possibilities, while a boolean query in the extended SSE scheme may contain \(i\) keywords (\(1 \leq i \leq d\)) and has \(\binom{d}{i}\) possible keyword combinations. Then, the probability that different search/update queries contain the same queried keywords set is relatively low. At the same time, even if there exist some such kind of queries, the obfuscating technique guarantees that it is difficult to link them as described in Section 5.1. Thus, from the perspective of probability, it is difficult to deduce the search pattern privacy when regarding all involved keywords as a whole. Therefore, the search pattern privacy of our extended SSE scheme is even stronger than that in our basic SSE scheme.

6 PERFORMANCE EVALUATION
In this section, we evaluate the performance of our proposed scheme with regard to the computational cost and communication overhead in search/update protocol, as well as the storage overhead at the client side. At the same time, we compare the computational cost of search queries between our proposed scheme and the most efficient implementation of a forward and backward private scheme so far (i.e., MITRA) [14]. Since our extended SSE scheme is based on our basic SSE scheme and has the similar performance as our basic SSE scheme, we focus on evaluating the performance of our basic SSE scheme. In specific, we implement our scheme in Java and conduct experiments on an Intel(R) Core(TM) i7-3770 CPU @3.40 GHz Windows Platform with 16 GB RAM. In our experiments, we respectively use HMAC-SHA1 as the PRF and a mersenne twister algorithm based generator as the PRG [17]. The secret key \(K\) is set to be a 160-bit random number, i.e., \(|K| = 160\). For the MITRA scheme, we evaluate it with the code released by authors [18]. In addition, we evaluate our scheme using synthetic dataset. Specifically, we randomly generate \(10^5\) keywords and each search/update operation involves \(k\) keywords, where the value of \(k\) is set to be 10, 20, 30. At the same time, we set the maximum number of documents in the system, i.e., \(N\), ranges from \(10^2\) to \(10^5\). All experiments were conducted 100 times and the average is reported.

6.1 Computational Cost
Search. As described in Section 4.2, the search protocol in our scheme consists of two rounds and all of the involved computational cost is at the client side. Suppose that \(C_{HMAC}\), \(C_{PRG}\) and \(C_{XOR}\) respectively denote the computational complexity of HMAC operation, pseudorandom number generation operation and XOR operation. Then, in the first round, the client requires \(k \times C_{HMAC}\) computational complexity to compute the locations associated with the current \(k\) queried keywords. In the second round, the client requires \(k \times (C_{HMAC} + C_{PRG} + C_{XOR})\) computational complexity to recover the documents’ identifiers matching the queried keywords. After that, he/she needs to re-encrypt the documents’ identifiers for each queried keyword and generate a new location for each encrypted documents’ identifiers with \(k \times (2 \cdot C_{HMAC} + C_{PRG} + C_{XOR})\). Thus, in the search protocol, the overall computational cost at the client side is \(k \times (4 \cdot C_{HMAC} + 2 \cdot C_{PRG} + 2 \cdot C_{XOR})\). Since pseudorandom number generation operation is to generate an \(N\)-bit binary string and XOR operation is over two \(N\)-bit binary strings, \(C_{PRG}\) and \(C_{XOR}\) are related to the parameter \(N\). Furthermore, the computational complexity of the search protocol is related to the anonymity parameter \(k\) and the maximum number of documents in the system \(N\). In Fig. 5a, we plot the average computational cost of our search protocol versus \(k\) and \(N\). From Fig. 5a, we can see that the search protocol is extremely efficient even if the runtime of search linearly increases as \(k\) and \(N\). For example, when \(k = 30\) and \(N = 10^5\), the runtime of each search operation is just 2.4 ms. Update. As described in Section 4.2, the update protocol also consists of two rounds and it executes almost the same operations as the search protocol, i.e., retrieve the data records matching the \(k\) queried keywords, re-encrypt them and send back to the server. The only difference is that the update protocol needs to additionally add/delete the updated document identifier, but the computational cost in this operation is low compared with other operations. Thus, the computational cost of the update protocol has the same trend but a little larger than that of the search protocol as shown in Fig. 5b.

Comparison With MITRA. In the literature, existing searchable encryption schemes can be divided into two categories, i.e., the ORAM and homomorphic encryption based schemes and SSE schemes. The ORAM and homomorphic encryption based schemes can achieve the same security level with our proposed scheme, i.e., simultaneously satisfy the forward privacy, backward privacy and search pattern privacy. However, compared with most of the SSE schemes, such kinds of schemes are computationally expensive and inefficient. Obviously, our proposed scheme is a SSE scheme and it is much more efficient than the ORAM and homomorphic encryption based schemes. As for the SSE based schemes, most of them cannot achieve backward privacy and none of them can achieve search pattern privacy, so they leak more privacy information than our proposed scheme. Thus, our proposed scheme leaks the least information.

In the following, we show that our proposed scheme is extremely efficient with regard to the search operation by comparing our scheme with the most efficient implementation of a forward and backward SSE scheme, i.e., MITRA. In specific, we compare the search efficiency between our proposed scheme and MITRA when variable \(N\) ranges from \(10^3\) to \(10^6\) and the size of the matched documents is set to be 1000 as shown in Fig. 5c. From Fig. 5c, we can see that our proposed scheme has better search performance than the
MITRA when the size of the matched documents is 1000. Therefore, our scheme achieves the best search efficiency.

Overall, our scheme not only achieves the best search efficiency, but also leaks the least information.

6.2 Communication Overhead

As described in Section 4.2, the search protocol and update protocol are two-round protocols and they involve the same communication overhead. In specific, in the first round, the client sends the locations of the queried keywords to the server. As HMAC-SHA1 is employed as PRF to generate these locations, the size of each location is 160 bits and the overall communication overhead for k locations is \( k \times 160 \) bits. At the same time, the server needs to return the encrypted values matched the requested locations to the client and each of them is \( N \) bits. Hence, the communication overhead for the encrypted values is \( k \times N \) bits. In the second round, the client returns \( k \) pairs new encrypted values and locations to the server and the communication overhead is \( k \times (2 \times 160 + 2 \times N) \) bits. Thus, the overall communication overhead in search/update protocol is \( k \times (2 \times 160 + 2 \times N) \). Fig. 6 plots the communication overhead of our search/update protocol versus \( k \) and \( N \). From Fig. 6, we can see that the communication overhead linearly increases as \( k \) and \( N \).

6.3 Client Storage

In our scheme, the client needs to locally store a 160-bit secret key and a map \( FileCnt \) containing \( d \) key-value pairs, where the value in the \( FileCnt \) is the number of times that each keyword is accessed (i.e., searched/updated). Suppose that the maximum number of times that a keyword is accessed is set to be \( N_{access} \). Then, the storage overhead at the client side is \( (160 + d \times \log_2 N_{access}) \) bits. When \( d = 10^4 \) and \( N_{access} = 10^7 \), the client’s storage overhead is roughly 8.77 KB.

7 RELATED WORK

With the explosive growth of data and enhancement of privacy awareness, more and more individuals and organizations choose to outsource encrypted data to the cloud. At the same time, in order to efficiently access and maintain the outsourced encrypted data, they expect to deploy a kind of encryption that can achieve privacy-preserving search and update over encrypted data, i.e., searchable encryption, which enables search over outsourced encrypted data and...
has attracted considerable attention from academia and industry. For the searchable encryption, security and efficiency are two main concerns and need to be balanced. In the literature, ORAM technique was deployed to design highly secure searchable encryption schemes, which can preserve all security concerns of encrypted data [6], [19]. Similarly, fully homomorphic encryption together with functional encryption also can be used to design highly secure searchable encryption [5]. However, the overhead of such schemes is too large and not practical.

SSE attempts to improve the search efficiency of searchable encryption scheme at the cost of small leakage including search pattern and access pattern. In 2000, Song et al. [4] proposed the first symmetric searchable encryption scheme and the search time over one document is linear to the length of the document. Then, Curtmola et al. [7] first defined the security of SSE, i.e., adaptive security of SSE and introduced the first inverted index based SSE scheme with sublinear search time. The inverted index technique builds a map from each keyword to the documents’ identifiers matching it, which is an important basis for many subsequent works.

However, the aforementioned proposals are static SSE schemes and they cannot support dynamical update of outsourced encrypted data. Compared with static SSE schemes, dynamic SSE schemes have rich functionality and are more desirable. In practice. In 2012, Kamara et al. [8] introduced the first dynamic SSE scheme with sub-linear search time, but this scheme reveals the updated document’s unique keywords. Then, Kamara and Papamanthou [9] designed a new dynamic SSE scheme to overcome the limitation in [8]. At the same time, Cash et al. [10] designed a dynamic SSE scheme for very-large databases.

Nevertheless, dynamic SSE schemes have more leakages than static SSE schemes including forward privacy and backward privacy. Forward privacy guarantees that the current update operation cannot be linked to previous search queries, which first introduced in [11]. Then, Stefanov et al. [20] introduced an ORAM based forward private scheme. Bost et al. [21] presented the formal definition of forward privacy and proposed an insertion-only scheme with optimal search and update complexity. Zhang et al. [12] presented a file-injection attack to reveal search queries by injecting few documents, and this attack is particularly effective, especially when the dynamical SSE is not forward private. From then on, the forward privacy becomes increasingly important in dynamic SSE. However, the authors pointed out that although the file-injection attack is effective and can be conducted easily in some system, it may be much more difficult to conduct such attack in the “closed systems”. This is because all documents in the “closed systems” are outsourced by the client and it is almost impossible for an adversary to inject documents into the systems, e.g., our proposed scheme.

The backward privacy guarantees that the current search keyword cannot be linked to the documents that match the search keyword but have been deleted before. Stefanov et al. [20] first introduced the notion of backward privacy to capture the leakage associated with deleted entries, but they neither described the definition of backward privacy nor presented a backward private SSE. Bost et al. presented a formal definition of backward privacy with three different types of leakages from most to least secure, and constructed four backward private SSE schemes that achieve different types of backward privacy [13]. Based on the work in [13], Chamani et al. [14] proposed three back-private constructions which improved the results of [13] in several ways. At the same time, Sun et al. [15] adopted the symmetric puncturable encryption technique to design a practical and non-interactive backward private SSE scheme. Recently, Zuo et al. proposed a dynamic SSE scheme with stronger backward privacy [22].

The above work focuses on the single keyword query. Although the single keyword query based SSE schemes can be easily extended to support complex queries, they are not efficient in complex queries. Thus, much of work on SSE focuses on supporting more complex query expressions such as multi-keyword query, boolean query, conjunctive query, disjunctive query and so on. Cash et al. [23] designed a SSE scheme to support conjunctive query and even boolean query. Faber et al. [24] extended the scheme in [23] to support more complex queries such as range query, substring query, wildcard query and phrase query. Pappas et al. [25] proposed a solution to support a rich query set including arbitrary boolean query and free keyword searches etc. Fisch et al. [26] proposed a SSE scheme to support boolean query and range query with sub-linear search time. Kamara et al. [27] and Lai et al. [28] respectively proposed a solution for disjunctive query and conjunctive query. Recently, Zuo et al. [29] designed two dynamic SSE schemes to support range queries and Shao et al. [30] proposed a verifiable scheme to support conjunctive and fuzzy queries.

8 Conclusion
In this paper, we have designed a practical SSE scheme with search pattern privacy, forward privacy and enhanced backward privacy, and extended it to support boolean queries. In specific, we leveraged k-anonymity and encryption technique to design an obfuscating technique. Then, based on the obfuscating technique, we deployed pseudorandom function and pseudorandom generator to design a single keyword queries based dynamic SSE scheme, and extended it to support efficient boolean queries. At the same time, we analyzed the security of our scheme and showed that the proposed scheme achieves desired security properties, i.e., search pattern privacy, forward privacy, and enhanced backward privacy. Besides, we conducted extensive experiment to evaluate the performance of our proposed scheme and the results showed that the proposed scheme is efficient in terms of communication overhead and computational cost. Our future work is to further improve the efficiency of search and update operations without weakening SSE scheme’s privacy preservation.

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