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# PRIVACY-PRESERVING IMAGE RETRIEVAL AND SHARING IN SOCIAL MULTIMEDIA APPLICATIONS

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***Abstract***— *Every day social multimedia applications generate millions of images. To handle such a huge amount of images, an optimal solution is using the public cloud, since it has powerful storage capability. Images usually contain a wealth of sensitive information, therefore social service providers need not only to provide services such as retrieval and sharing but also to protect the privacies of the images. In this paper, we propose a privacy-preserving scheme for content-based image retrieval and sharing in social multimedia applications. First, the users extract visual features from the images, and perform locality-sensitive hashing functions on visual features to generate image profile vectors. We then model the retrieval on the images as the equality search on the image profile vectors. To enable accurate and efficient retrieval, we design the secure index structure based on cuckoo hashing, which has constant lookup time. To meet the requirements of dynamic image updating, we enrich our service with image insertion and deletion. In order to reduce the key management overhead and the access control overhead in social applications, we process keys using secret sharing techniques to enable the users holding similar images to query and decrypt images independently. Finally we implement the prototype of the proposed scheme, and perform experiments over encrypted image databases.*

*Keywords — Image retrieval, image sharing, multimedia, privacy-preserving.*

## I. INTRODUCTION

Due to the popularity of mobile devices with cameras, such as mobile phones, tablets, sensors, and etc., the amount of images has grown tremendously. Specifically, social multimedia applications, that provide platforms to post and share multimedia, generate massive amounts of images. According to Instagram, more than 100 million images are posted per day [1]. Due to the high storage costs, social service providers prefer to outsource such a massive amount of images to public cloud platforms such as Amazon Cloud. Images usually contain sensitive information that could reveal personal privacies, and encryption is an effective method to protect privacy. Based on cryptography, a number of privacy-preserving schemes [2]–[7] that support remote image retrieval and sharing have been proposed. The social multimedia application is becoming one of the main platforms for image retrieval and

sharing, this paper proposes a privacy-preserving image retrieval and sharing scheme for social multimedia applications. The contributions of this paper can be summarized as follows: •We propose a privacy-preserving content-based image retrieval and sharing scheme for social multimedia applications. The scheme allows the image owners to outsource images to the public cloud server, and outsource secure index to the social service provider.

.•Our scheme is constructed under a stronger and more realistic threat model that the social service provider is not a completely trusted entity. The social service provider is allowed to acquire a part of the users' information, but it cannot be trusted to store the keys.

• Our scheme greatly simplifies access control and key management in multi-user social applications. We allow the users holding similar images to submit the retrieval queries, and decrypt the query results on their own.

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• We design a secure index that provides efficient retrieval service for large image sets. The index requires constant lookup time and supports dynamic image updating.

## II. RELATED WORK

Content-based image retrieval (CBIR) [8] using the content of query images to search for similar images is a main research branch in the area ofimage retrieval. In CBIR, one key work is to extract visual features from the images for image representation and similarity measurement. In previous works, high-dimensional local features such as SIFT [9], SURF [10], ORB [11], etc. have been extensively explored as a routine image representation, and have beenas keys for encryption to simplify key managem proved to be effective in CBIR. Searchable encryption (SE) was proposed to protect data privacy on the remote server side, while preserving search ability. And not limited to file and texture, the data types studied in SE have been extended to image. However, when image sources are diverse and authorized users are diverse, access control and key management are challenging problems in SE. In terms of access control, it usually requires image owners to predefine access policies for their images. Xia et al. [2] and Xu et al. [3] required the users to request authentication from the image owner before performing the query. Yuan et al. [4] distributed roles for the users and created search policies to decide who can search a particular image with these roles. In terms of key management, one solution is to allow image owners to manage their own keys. The schemes proposed by Zou et al. [5] and Wang et al. [6] required the image owners to store their own keys, and the users can not independently decrypt the encrypted images without additional interaction with the image owners. Another solution is to introduce third party entities for key management. The scheme proposed by Li et al.
[7] required non-colluding entities that perform cryptographic computations to handle key management. Moreover, in social multimedia applications, which involve large numbers of users and huge amounts of images, the common solution is to let the social service providers manage the keys. Under the assumption that the social service providers are trusted entities, Yuan et al. [13] and Ahmed et al.
designed privacy-preserving image-centric social discovery schemes, which give the secret keys to the social service providers for storage and delegate the decryption operations to the social service providers. However, such anassumption is not always reasonable in real-world applications. Usually, social service providers cannot be completely trusted, therefore the outsourced private information is facing the risks of privacy leakage and abuse. For example, on April 18, 2019,Facebook announced that millions of Instagram passwords were stored in a readable format and could be accessed by Facebook employees [15].

Pieters and Tang [16] proposed a (k, n) threshold data-based access control paradigm, where the access to information is based on the similarity between the information being accessed and the information provided to access it. Specifically, if k of n data-items are the same, the information being accessed can be recovered from the information provided to access it. Boldyreva et al. [17] came up with the similar idea and proposed the concept of keyless fuzzy search (KlFS) which can be applied to the images. KlFS masks databases in such a way that the user can retrieve a masked database and unmask the data if and only if it possesses some data that is ‘‘close to’’ the encrypted data. Inspired by the ideas of [16], [17], we use t-out-

of-n secret sharing technique for access control and decryption to reduce the costs of key management and access control. The rest of our paper is organized as follows: Section III reviews some preliminaries of this paper. Section IV presents the system overview. Section V proposes the detailed design of our scheme. Section VI gives security analysis and efficiency analysis. Section VII evaluates the performance of our scheme. Finally, Section VIII concludes the paper.

## III. PRELIMINARIES

In this section, we introduce the basic primitives that are used in our privacy-preserving image retrieval and sharing scheme.

### A. EXTENDEDLOCALITY-SENSITIVEHashi ng(eLSH)

Locality-Sensitive Hashing(LSH) [18] is a common algorithm used to solve the approximate nearest neighbor search in high-dimensional spaces. The high dimensionality of high-dimensional data results in high search time cost or high space overhead. LSH, which maps similar objects into the same hash buckets with high probability and reduces the dimensionality of data, has become a promising approach to similarity search in high-dimensional spaces [19]–[21]. In this paper, to amplify the accuracy of the parameters, an extension of LSH, i.e. eLSH, is adopted. Definition 1 [Locality-Sensitive Hashing (LSH)]: Given threshold values δ C and δ F , where δ C < δF , and probability values p1 and p2, where p1 < p2, the locality sensitive hash family H = {h : D → U} is called (δ C, δF , p1, p2)−sensitive if the following holds: for a distance function d, and for any x, y ∈ D, if d(x, y) 6 δ C then PrH [h(x) = h(y)] > p1; if d(x, y) > δF then PrH [h(x) = h(y)] 6 p2.

Definition 2 [Extended Locality-Sensitive Hashing (eLSH)]: Given (δ C, δF , p1, p2)−sensitive hash family H, and positive integers k and L. For i ∈ [L] and j ∈ [k], the hash function gi(x) is defined as gi(x) = (hi1(x), hi2(x), . . . , hik (x)), where hij ∈ H. The set {g1, g2, . . . , gL} is called the (L, k) − eLSH [22] and satisfies the following. For a distance function d, and for any x, y ∈ D, if d(x, y) 6 δ C, then Pr[∃i ∈ [L] : gi(x) = gi(y)] > 1 − (1 − p1 k ) L = P1; if d(x, y) > δF , then Pr[∃i ∈ [L] : gi(x) = gi(y)] 6 1 − (1 − p2 k ) L = P2.

In eLSH, the concatenation of k functions reduces the chance of collision between similar items and the set of L functions improves recall.

### B. CUCKOO HASHING

Cuckoo hashing [23] is a dictionary scheme that uses two or more hash functions instead of only one to resolve hash collisions. It can balance the load and support efficient queries with constant lookup time in the worst case. Definition 3 (Standard Cuckoo Hashing): Cuckoo Hashing has two hash tables, T1 and T2, which are associated with hash functions f1 and f2, respectively. In addition, each hash table has w buckets. An item x can be inserted into either the bucket T1[f1(x)] of T1 or the bucket T2[f2(x)] of T2. Definition 4 (Improved Cuckoo Hashing):
Improved Cuckoo Hashing [24] has l (l > 2) hash tables {T1, T2, . . . , Tl}, where each table Ti has a hash function fi and w buckets. An item x can be inserted into the bucket Ti[fi(x)] of Ti , where i

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∈ [l]. Give a simple example to explain cuckoo hashing. When inserting item c into the standard cuckoo hashing, if either of two available positions T1[f1(c)] and T2[f2(c)] is empty, c will be inserted. If the two available positions are occupied by a and b, c kicks away a or b and reinserts a or b. C.

## SECRET SHARING

Secret sharing [25] is a cryptographic method that divides data into n pieces, and distributes pieces among n participants, so that the secret can be reconstructed by cooperation of no less than t participants. In terms of privacy, participants holding less than t pieces learns no more information about the secret than knowing no piece. A t-out-of-n secret sharing scheme is defined by algorithms (Share, Reconst), where Share is the secret sharing algorithm and Reconst is the reconstruction algorithm. Share: It takes as input a secret s, and outputs a set of pieces {p1, p2, . . . , pn}. Reconst: It takes as input a set of pieces {p1, p2, . . . , pm}, and outputs s if m > t, or ⊥ if m < t. D.

**CLOSENESS DOMAINS** D is defined as either a finite or an infinite domain, and Cl is defined as the symmetric (partial) closeness function that takes any x, y ∈ D as input and outputs a member of {close, far}. For a distance function d, closeness parameters are defined as
δ C and δ F , where δ C < δF . The closeness domain (D,Cl) [26] is defined as follows. For any x, y ∈ D,
Cl(x, y)= {( close, if d(x, y) 6 δ
C far, if d(x, y) > δF

## IV. SYSTEM OVERVIEW

To get closer to reality, we treat the social service providers as incompletely trusted entities. And under such assumption, we design privacy-preserving image retrieval and sharing schemes for social multimedia applications.

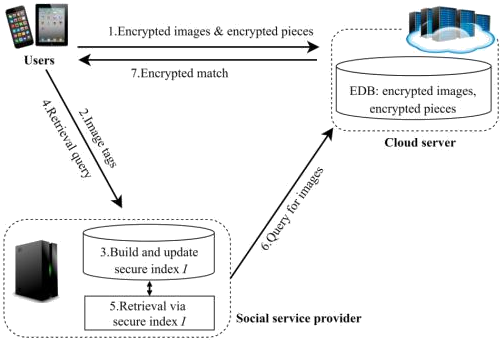


***FIGURE 1. System architecture***

To support efficient retrieval on large-scale images, we use cuckoo hashing to design efficient indexes. To reduce the costs of key management and access control caused by multi users in social applications, we use the idea of KlFS to process the images. The intuition of our scheme is using image content to search for similar images and share images. In social multimedia applications, if two users post images with similar content, such as the same restaurant they went to, the same poster they like, or the same movie they saw, they are very likely to have similar interests and they can be potential friends.

For example, Alice posts the images about her mountain climbing, then she may want to search for

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mountaineering enthusiasts through the posted images, and further discuss climbing skills or meet up with a mountain trip. So our scheme can be extended to friend recommendation and other applications.

## A. ARCHITECTURE AND ENTITIES

Fig.1. illustrates the architecture of our scheme at a high-level. The scheme involves three entities: the users, the social multimedia application server (SS), and the cloud server (CS). The users are mobile terminals with a certain level of computing power, such as laptop, smartphone, tablet, and etc. The SS is the internal server of a social service provider that offers social multimedia services to the users, such as Instagram, Facebook, Flickr, and etc. The CS is a third-party cloud server such as Amazon cloud.

## B. SERVICE FLOW

As shown in Fig.1, the service flow of our scheme involves 4 phases: 1) Imagepreprocessing (steps 1&2): A user first encrypts his images. Then the user extracts visual features from the images and calculates the profile vectors from the visual features. To simplify the key management, the user uses a secret sharing scheme to share the keys that used to encrypt the images, and encrypts all the pieces using the profile vectors. Then the user uploads both the encrypted images and the encrypted pieces to the CS. Meantime, the user derives the tags that used for similarity retrieval from the profile vectors, and transfers the tags to the SS.

| Notations | Descriptions |
|---|---|
| $I$ | The image |
| $I^*$ | The encrypted image |
| $m$ | The threshold value for secret sharing |
| $K$ | The symmetric secret key |
| $\mathcal{I}$ | The secure index |
| $n$ | The pieces number, the extracted features number |
| $N$ | The size of the image set |
| $L, k$ | The parameters of *eLSH* |
| $g_i()=(h_{i1}(),h_{i2}(),\ldots,h_{ik}())$ | The $i$-th hash function of *eLSH*, $i \in [L]$ |
| $V=\{v_1, v_2, ..., v_n\}$ | The image feature vector set |
| $Piece=\{p_1, p_2, ..., p_n\}$ | The secret piece set of $K$ |
| $M_i=\{m_{i1}, m_{i2}, ..., m_{iL}\}$ | The profile vector set of $v_i$, $i \in [n]$ |
| $sk_{ij}$ | The secret key derived from $m_{ij}$, $i \in [n]$, $j \in [L]$ |
| $p^*_{ij}$ | The encrypted piece calculated by $p_i$ and $sk_{ij}$, $i \in [n]$, $j \in [L]$ |
| $Piece^*$ | The encrypted piece set of $K$ |
| $tag_{ij}$ | One tag of $v_i$, derived from $m_{ij}$, $i \in [n]$, $j \in [L]$ |
| $Tag$ | The tag set of the image |
| $T=\{T_1, T_2, ..., T_l\}$ | The cuckoo hashing with $l$ hash tables |
| $d$ | The probe value of the cuckoo hashing |
| $H, G$ | Two secure pseudo-random functions |

2) Index Update (step 3): Upon receiving the tags from the user, the SS inserts the tags into the index. 3) Image retrieval (steps 4&5): For the retrieval query from the user, the SS performs similarity retrieval via the index. 4) Image sharing (steps 6&7): After getting retrieval results, the SS asks the CS to return the corresponding encrypted images and the encrypted pieces to the user. The user reconstructs the keys and decrypts the images.

## C. DEFINITION AND NOTATION

Before presenting the definition of our scheme, we first define some notations, as listed in Table 1, which will be used in our following definition and constructions. Then we formally define our notion of Privacy-preserving Image Retrieval and Sharing scheme in Social Multimedia applications.

Definition 5 (Privacy-Preserving Image Retrieval and Sharing): A privacy-preserving image retrieval and

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sharing scheme in social multimedia applications consists of the following algorithms or protocols.

• **Setup**(1λ , params) → (PFuncs, T ): Run by the SS. It takes as input a security parameter λ and function initialization parameters params. It outputs public functions PFuncs and a cuckoo hashing T .

• **ImageProcess**(1λ , PFuncs, I) → (I ∗ , idI , Piece∗ , Tag): Run by the user. It takes as input a security parameter λ, public functions PFuncs and the image I. It outputs the encrypted image I
∗ , the image identifier idI , the encrypted piece set Piece∗ , and the tag set Tag
. • **IndexGen**(T , Tag) → I: Run by the SS. It takes as input the cuckoo hashing T and the tag set Tag. It outputs the secure index I.

• **EDBGen**(idI , I ∗ , Piece∗ ) → EDB: Run by the CS. It takes as input the image identifier idI , the encrypted.
image I ∗ , and the encrypted piece set Piece∗ . It outputs the encrypted database EDB.

• **QueryGen**(PFuncs,I) → Tag: Run by the user. It takes as input the public functions PFuncs and the query image I. It outputs the query token Tag.

• **Retrieval(**Tag, I) → ({I ∗ },{Piece∗ },AUX): Run by the SS and CS. It takes as input the query token Tag and the secure index I. It outputs the encrypted similar images {I ∗ }, the corresponding encrypted piece sets {Piece∗ }, and the auxiliary information set AUX.

• **ImageRecover**(I ∗ o , Piece∗ , I,AUX, PFuncs) → Io: Run by the user. It takes as input the encrypted image I ∗ o , the corresponding encrypted piece set Piece∗ , the query image I, the auxiliary information set AUX, and public functions PFunds. It outputs the image Io.

We also formally define our notion of Image Similarity. Definition 6 (Image Similarity): For two images I1 and I2, V1 = {v1, v2, . . . , vn} and V2 = {v 0 1 , v 0 2 , . . . , v 0 n } are feature vector sets extracted from I1 and I2, respectively. For two feature vectors v and v 0 , if they have the same (L, k) − eLSH value, Cl(v, v 0 ) = close and v and v 0 are considered similar. If I1 and I2 have no less than m similar feature vectors, Cl(I1, I2) = close and I1 and I2 are considered similar.

**D. THREAT MODEL** In our scheme, we suppose the CS and the SS are two non colluding ‘‘honest-but-curious’’ adversaries. We first consider the primary security threat from the CS. The CS is assumed to follow the specified service flow faithfully, but it intends to learn the content of the images, the profile vectors of the visual features, and the keys for the images. We focus on preserving the confidentiality of the images and the key pieces outsourced in the CS. The SS is also assumed to follow the scheme faithfully, but it also intends to infer the keys and the visual features. We should ensure that the SS cannot acquire the keys, and the tags do not reveal the content of the visual features. For the users, we assume that they are trustworthy and can preserve their secrets, including the keys, the visual features, and the profile vectors.

## V. CONSTRUCTION

We propose the detailed construction of our privacy preserving image retrieval and sharing scheme in social multimedia applications.

1) **Setup**(1λ , params) → (PFuncs, T ): Given a security parameter λ, the SS initializes Pseudo-Random Functions (PRF) H and G. Given function initialization parameters params = {L, k, m, n, l,w, u}, SS initializes an extended locality-sensitive hashing (L, k) − eLSH, a m-out-of-n secret sharing scheme (Share, Reconst), and a cuckoo hashing T = {T1, T2, . . .

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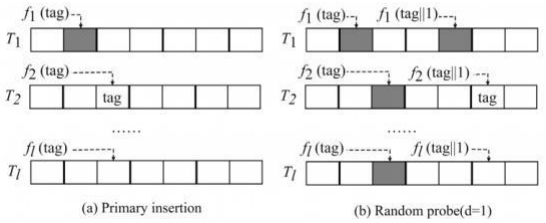
, Tl} with l hash tables. Each table Ti has a hash function fi and w buckets, where each bucket is u−bit in length. Then the SS sets PFuncs = {H, G, (L, k) − eLSH, (Share, Reconst)} as the public functions and makes PKFuncs public.




2) **ImageProcess**(1λ , PFuncs, I) → (I ∗ , idI , Piece∗ , Tag): Before uploading images to the social multimedia application, the user takes the following steps to process the image.
3)Image encryption: The user first generates identifier idI for the image I. Then given a security parameter λ, the user chooses a secret key K for the image I, and invokes semantic secure symmetric encryption algorithm to encrypt I and obtains the encrypted image I ∗
. • Secret key sharing: The user performs Piece ← Share(K), where Piece = {p1, p2, . . . , pn} is the secret piece set.

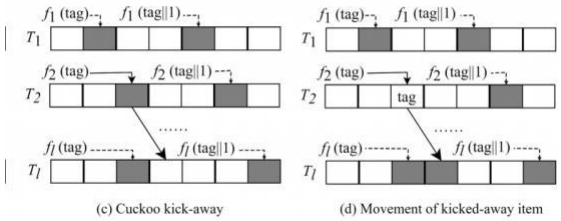
Profile generation: From the image I, the user extracts the feature vector set V = {v1, v2, . . . , vn}, e.g. ORB, SURF, and etc. Note that, the number of the extracted feature vectors is equal to the number of K's pieces. For each vi in V, the user performs (L, k) − eLSH to generate the profile vector set Mi = {mi1, mi2, . . . , miL}, where mij = gj(vi) = {hj1(vi), hj2(vi), . . . , hjk (vi)}, i ∈ [n] and j ∈ [L].

Tags generation: For each mij in Mi , the user performs tagij ← H(mij) and appends {tagij, idI , i, j} to the tag set Tag of the image I, where tag is used for equality matching in retrieval, idI is the image identifier, i is the feature identifier, and j is the eLSH identifier which indicates that the j-th hash function gj() of eLSH is used for generating mij. After performing the above operations on all profile vectors of I, the user gets the tag set Tag of the image I.

Pieces encryption: For each mij in Mi , the user performs skij ← G(mij) and gets the secret key skij. Then the user invokes symmetric encryption algorithm p ∗ ij ← Enc(skij, pi) to encrypt the secret piece pi of K. The user appends the encryption result p ∗ ij to Piece∗ , i.e. the encrypted piece set of I. After performing the above operations on all profile vectors, the user gets the encrypted piece set Piece∗ of the image I.

Finally, the user uploads the encrypted image I ∗ and the encrypted piece set Piece∗ to the CS, and uploads Tag to the SS.

3) **IndexGen**(T , Tag) → I: Given the cuckoo hashing T , the SS takes the following steps to insert Tag into it and



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construct the secure index I. The specific algorithm is described in Algorithm 1 and the index design is illustrated in Fig. 2. For each item = {tag, idimage, id feature, ideLSH } in Tag:

• Primary insertion: the SS tries to insert an item into one of the l hash tables. The SS first initializes two sets, Occupied = ∅ and Whole = {1, 2, . . . , l}. Then it randomly picks an i ∈ Whole. If the bucket Ti[fi(tag)] is empty, the SS inserts item into Ti[fi(tag)] and the insertion is finished; otherwise, if the bucket Ti[fi(tag)] is occupied, the SS appends i to Occupied and update Whole = Whole − Occupied. The SS repeats the above operations iteratively until item is inserted into I or Whole = ∅.

• Random probe: If none of the above l buckets is empty, then the SS expands the number of target buckets to d +1 for each hash table. The SS initializes Occupied = ∅ and Whole = {1, 2, . . . , l}. The SS first randomly picks an i ∈ Whole. Then for each δ ∈ [1, d], if the bucket Ti[fi(tag k δ)] is empty, the SS inserts item into Ti[fi(tag k δ)] and the insertion is finished; otherwise, if all of d buckets are occupied, the SS appends i to Occupied and update Whole = Whole − Occupied. SS repeats the above operation iteratively until item is inserted into I or Whole = ∅.

• Cuckoo kick-away: If all of the above l + l × d buckets are occupied, the SS randomly selects an i ∈ [l] and kicks away the item Kicked Out stored in Ti[fi(tag)]. Then the SS inserts the item into the bucket Ti[fi(tag)] and re-inserts Kickedout back via the above steps iteratively. After performing the above operations on all t ags in Tag, the index I is updated.

4) **EDBGen**(idI , I ∗ , Piece∗ ) → EDB: Given the image identifier idI , the CS maps it to an address AddI in the cloud storage. Then the CS stores I ∗ and Piece∗ at AddI .

5) **QueryGen**(PFuncs,I) → Tag: The user first extracts the feature vector set V = {v1, v2, . . . , vn} from the query image I. Then for each vi in V, the user performs (L, k) − eLSH to generate the profile vector set Mi = {mi1, mi2, . . . , miL}. Finally for each mij in Mi , the user performs tagij ← H(mij) and generates the tag set Tag. The user sends Tag to the SS for retrieval.

6) **Retrieval(**Tag, I) → ({I ∗ },{Piece∗ },AUX): After receiving Tag of the query image I, the SS takes the following steps to retrieve similar images and asks the CS to return the user the encrypted images. The specific protocol is described in Algorithm 2.

• Trapdoor generation: For each item = {tagij, idI , i, j} in Tag of the query image I, where i ∈ [n] and j ∈ [L], the SS transforms it into a trapdoor t = {(t 0 1 , . . . , t d 1 ), . . . (t 0 l , . . . , t d l )}, where t δ η = fη(tagij k ϕ), ϕ = ∅ if δ = 0, ϕ = δ if δ ∈ [d]. After performing the above operations on all tags in Tag, the SS gets t, which consists of n × L trapdoors t.

• Bucket location: For t δ η in t, where η ∈ [l] and δ ∈ [d], the SS locates the bucket Tη[t δ η ]. If item = {tagij, idI , i, j}, that is used to generate t, and {tag, idimage, id feature, ideLSH }, that is the content of Tη[t δ η ], have the same eLSH identifier, i.e. ideLSH = j, then SS appends {idimage, id feature, i, j} to the intermediate result set IR. The SS repeats the above operations on all t of t and updates IR.

• Threshold filtering: For each image id image that exists in the IR, the SS counts the number of similar feature vectors between idI and idimage. If the number of similar features is greater than or equal to the threshold value m, the SS adds the image identifier idimage to the query result set QR, and appends all items {idimage, id feature, i, j} associated with damage to the auxiliary information set AUX. Finally, the SS sends QR to the CS for requesting images, and returns AUX to the user for speeding up the decryption operation.

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• Query for images: After receiving query result set QR from the SS, the CS retrieves encrypted database EDB. For each image identifier image in QR, the CS maps it to the address Addimage and obtains I ∗ image and Piece∗ image stored at Addimage. After performing the above operations on all identifiers in QR, the CS gets all encrypted similar images {I ∗ } and the corresponding encrypted piece set{Piece∗ }. Finally the CS returns them to the user.

7) **ImageRecover**(I ∗ o , Piece∗ , I,AUX, PFuncs) → Io: For the encrypted image I ∗ o and the corresponding encrypted piece set Piece∗ , the user takes the following steps to recover the image.

• Pieces recovery: For each item {idIo , id feature, i, j} in AUX corresponds to the encrypted image I ∗ o , the user first performs skij ← G(mij), where mij of the query image I has been calculated in the QueryGen step. Then the user invokes symmetric decryption algorithm pid feature ← Dec(skij, p ∗ idfeature,j ) and obtains the secret piece pid feature . After performing the above operations on all of the items correlative to I ∗ o in AUX, the user recovers at least m pieces, i.e. {p1, p2, . . . , pm∗ }, where m ∗ > m.

• Secret key reconstruction: The user performs the algorithm K ← Reconst(p1, p2, . . . , pm∗ ).

**Algorithm1**IndexGeneration

**Input**: Tag = {{tag11, . . . , tag1L }, . . . ,{tagn1 , . . . , tagnL}}: the tag set of the inserted image, T : the cuckoo hashing

**Output**: Updated secure index I

1: function INSERTIDX(Tag, T )
2: for i ← 1 to n do
3: for j ← 1 to L do
4: Insert:
5: Occupied ← ∅;
6: Whole ← {1, 2, . . . , l};
7: while Whole 6= ∅ do
8: Randomly pick k ∈ Whole;
9: if Tk [fk (tagij)] = NULL then
10: Tk [fk (tagij)] ← tagij
11: goto:Next;
12: end if
13: Append k to Occupied;
14: Whole ←Whole−Occupied;
15: end while
16: Occupied ← ∅;
17: Whole ← {1, 2, . . . , l};
18: while Whole 6= ∅ do
19: Randomly pick k ∈ Whole;
20: for δ ← 1 to d do
21: if Tk [fk (tagij||δ)] = NULL then

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22: Tk [fk (tagij||δ)] ← tagij;
23: goto:Next;
24: end if
25: end for
26: Append k to Occupied;
27: Whole ←Whole−Occupied;
28: end while
29: Randomly pick k ∈ [l];
30: Kickedout ← Tk [fk (tagij)];
31: Tk [fk (tagij)] ← tagij;
32: goto:Insert; // insert Kickedout
33: Next:
34: end for
35: end for
36: end function

Image decryption: The user invokes symmetric decryption algorithm to decrypt I ∗ o with K, and obtains the image Io.

Image Update: As the user adds or deletes the image, not only the encrypted database stored in the CS should be updated, but also the secure index stored in the SS is updated. For image addition, Tag of the added image should be inserted into I. The SS inserts Tag into the cuckoo hashing following the steps in IndexGen. For image deletion, Tag of the deleted image should be removed from I. First the SS performs trapdoor generation to generate t and locates n
L × l × (d + 1) buckets according to the steps in Retrieval. Then the SS checks whether the items stored in these buckets belongAlgorithm 2 Image Retrieval

Input: Tag = {{tag11, . . . , tag1L }, . . . ,{tagn1 , .
. . , tagnL}}: the query token, I: the secure index Output: {I ∗ }: the encrypted similar images, {Piece∗ }: the corresponding encrypted piece set; AUX: auxiliary information set.

1: function RETRIEVAL(Tag, I)
2: Retrieval on SS:
3: IR←∅
4: for tagij in Tag do
5: for k ← 1 to l do
6: for δ ← 0 to d do
7: if δ = 0 then
8: ϕ=∅;
9: else
10: ϕ=δ;
11: end if
12: t δ k=fk (tagij k δ);

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13: (tag,idimage,idfeature,ideLSH )←Tk [t δ k ];
14: if ideLSH=j then
15: R← {idimage, idfeature, i, j};
16: Append R to IR;
17: end if
18: end for
19: end for
20: end for
21: countdict← dict();
22: aux← invertedindex();
23: for R in IR do
24: if R.idimage ∈ countdict then
25: countdict[R.idimage]+=1;
26: Append R to aux[R.idimage];
27: else
28: countdict[R.idimage]=1;
29: Append R to aux[R.idimage];
30: end if
31: end for
32: QR←∅;
33: AUX←∅;
34: for idimage in countdict do
35: if countdict[idimage]>m then
36: Append idimage to QR;
37: Append aux[idimage] to AUX;
38: end if
39: end for
40: Retrieval on CS:
41: {I ∗ }←∅;
42: {Piece∗ }←∅;
43: for idimage in QR do
44: Addimage←map(idimage);
45: Read (I ∗ image, Piece∗ image) at Addimage;
46: Append I ∗ image, Piece∗ image to {I ∗ }& {Piece∗ };
47: end for 48: end function

to Tag. For the items belong to Tag, the SS deletes the items and empties the corresponding buckets.

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## VI. ANALYSIS OF THE PROPOSED SCHEME

### A. SECURITY ANALYSIS

In our scheme, there are two non-colluding and ‘‘honest-butcurious’’ servers. We first quantify the information leakage in the view of the SS and the CS respectively, and then demonstrate that neither the SS nor the CS can infer any extra information from their views.

First, we quantify the information leakage in the view of the SS. The SS stores the secure index I, and handles the image retrieval. The leakage patterns obtained by the SS include the closeness pattern which is inferred from the index I, the search pattern which is inferred from the retrieval queries, and the access pattern which is inferred from the retrieval operations. The formal definitions are as follows.
Definition 7 [Closeness Pattern (CP)]: For all images {I1, I2, . . . ,IN } inserted into the index I, CP is defined as a symmetric matrix CPN×N , where the element CPN×N [i][j] is a list that records the identifiers of the similar features between two images and the identifier of eLSH that results in the same tag of these two similar features. For 1 6 i, j 6 N, if Ii and Ij have no similar feature, CPN×N [i][j] = ∅, otherwise, for tagkη ∈ Ii and taglη ∈ Ij , if tagkη = taglη , (k, l, η) is an element of CPN×N [i][j].
Definition 8 [Search Pattern (SP)]: For a set of q queries {Tag1 , Tag2 , . . . , Tagq }, SP is defined as a symmetric matrix SPq×q, where the element SPq×q[i][j] is a list that records the identifiers of the similar features between two queries and the identifier of the eLSH that results in the same tag of these two similar features. For 1 6 i, j 6 q, if Tagi and Tagj have no similar feature, SPq×q[i][j] = ∅, otherwise, for agkη ∈ Tagi and taglη ∈ Tagj , if tagkη = taglη , (k, l, η) is an element of SPq×q[i][j].

Definition 9 [Access Pattern (AP)]: For a set of q queries {Tag1 , Tag2 , . . . , Tagq }, AP is defined as(B, AP(q+ω)×(q+ω)). B = ({B1},{B2}, . . .

,{Bq}), where {Bι} is the accessed buckets of Tagι . AP(q+ω)×(q+ω) is a symmetric matrix, where ω is the number of image identifiers appeared in B and the element AP(q+ω)×(q+ω)[i][j] is a list that records the identifiers of similar features between two images and the identifier of the eLSH that results in the same tag of these two similar features. For 1 6 i, j 6 q + ω, SubTagi and SubTagj are the subsets of Tagi and Tagj , which are inferred from the queries and B. If SubTagi and SubTagj have no similar feature, AP(q+ω)×(q+ω)[i][j] = ∅, otherwise, for tagkη ∈ SubTagi and taglη ∈ SubTagj , if tagkη = taglη , (k, l, η) is an element of AP(q+ω)×(q+ω)[i][j]. Definition 10 [View of SS (VSS )]: VSS is the information leakage obtained by SS for a set of q queries, and defined as VSS = (I, CP, SP, AP). Theorem 1 (Indistinguishability for SS): Let A be a probabilistic polynomial-time (P.P.T.) adversary, SimSS be a P.P.T. simulator, and VeSS is the simulated view. For a set of q queries, we have |Pr[A(VSS ) = 1] − Pr[A(VeSS )
1]| < , where is negligible, i.e., VSS and VeSS are computationally indistinguishable. Proof: We first give the process of the simulating view VeSS : • Simulation of index eI. SimSS generates l hash tables, and each table contains w buckets. i.e., eI has the same size as I. Recall that the items stored in the buckets of I contain tag, the identifier of the image, the identifier of the feature, and the identifier of the eLSH. Therefore, for each occupied bucket of I, according to the closeness pattern CP of I, SimSS first generates a random string tagf that has the same length with tag, and then generates three random strings as the identifiers that has the same lengths with the real ones. • Simulation of trapdoors and accessed buckets for a set of q queries. For each item in the query q1, SimSS simulates a trapdoor et1 = {( et 0 1 , . . . , et d 1 ),

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( et 0 2 , . . . , et d 2 ), . . . ( et 0 l , . . . , et d l )}, where et δ η is a random string that has the same length as the real one. According to the access pattern AP, for et1, SimSS simulates the accessed buckets {Be1}, where the number of simulated buckets is equal to the number of real ones. For queries qi+1 (1≤i≤ q-1), SimSS adaptively simulates trapdoorseti+1 according to the search pattern SP obtained from the previous i queries. For the subcomponent ofeti+1 that has not appeared in the previous queries, SimSS adopts the above approach to generate a random string as the subcomponent and then SimSS adopts the same approach to simulate accessed buckets via AP. For subcomponent ofeti+1 that appeared before, SimSS uses the same string used before and the same bucket for simulation. Due to the pseudo-randomness of the secure PRFs, tagf and tag,eI and I,et and t,eB and B are indistinguishable. Therefore, the simulated view VeSS is indistinguishable from VSS . Then, we quantify the information leakage in the view of the CS. The CS stores the encrypted images and the encrypted pieces, and responds to the request of the SS. Definition 11 [View of CS (VCS )]: VCS is the information leakage obtained by the CS and is defined as VCS = EDB, where EDB includes the encrypted images (I ∗ 1 , I ∗ 2 , . . . ,I ∗ N ) and the encrypted pieces (Piece∗ 1 , Piece∗ 2 , . . . , Piece∗ N ). Theorem 2 (Indistinguishability for CS): Let A be a P.P.T. adversary, SimCS be a P.P.T. simulator, and VeCS is the simulated view. For a negligible we have |Pr[A(VCS ) = 1] − Pr[A(VeCS ) = 1]| < i.e., VCS and VeCS are computationally indistinguishable. Proof: SimCS can simulate EDB g according to VCS . For the storage at each address, SimCS first generates a random string Ie∗ that has the same length as I ∗ . Then SimCS generates random strings Piece ^∗ that has the same length as the encrypted pieces Piece∗ . Due to semantic security of the symmetric encryption, Ie∗ and I ∗ , Piece ^∗ and Piece∗ are indistinguishable. Therefore, the simulated view VeCS is indistinguishable from VCS .

**TABLE 2. Performance comparison.**

| | Our scheme | Scheme of [5] |
|---|---|---|
| Index size | $O(NnL)$ | $O(N)+O(N)$ |
| Retrieval time | $O(1)$ | $O(N)+O(\delta)$ |
| Imageprocess comp. | $(2nL)PRF+(nLk)LSH$ $+1SS+(nL)ENC$ | $(n+3nk)PRF$ |
| QueryGen comp. | $(nL)PRF+(nLk)LSH$ | $(n+3nk)PRF$ |
| Retrieval comp. | $nLl\cdot(d+1)(PRF+CP)$ | $(N+\delta)CP+\delta MUL$ $+(2nk)PRF$ |
| ImageRecover comp. | $(m+1)DEC+mPRF+1SR$ | $1DEC$ |
| User&owner Comm. | $--$ | 1 |

## B.EFFICIENCY ANALYSIS

In this section, we discuss the performance of our scheme and make comparisons to the scheme proposed by Zou et al. [5] that is most similar to ours.

The factors we focus on to evaluate performance include the index size, retrieval time, image processing computation, query generation computation, retrieval computation,

image recovery computation, and communication times between the image owner and the user. Table 2 summarizes the complexity or the operations required for these phases, where PRF denotes evaluation of a pseudo-random function, LSH denotes evaluation of a locality-sensitive hashing, CP denotes a numerical comparison, MUL denotes a multiplication operation, ENC denotes a symmetric encryption operation, DEC denotes a symmetric decryption operation, SS denotes a sharing operation in secret sharing, SR

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denotes a reconstruction operation in secret sharing, N denotes the total number of images, and δ denotes the number of matched images in the first round of comparison in [5].

Owing to the properties of cuckoo hashing, our retrieval time O(1) is constant and our index size O(NnL) is linearly increased with the number of tags in N images. Suppose the index load factor is defined as $\tau = p/lw$, where p is the number of occupied buckets, and lw is the size of the cuckoo hashing. So the size of our index design is $(NnL)\cdot u/\tau$ , where u is the bit length of each bucket. In the process of image processing, the user performs $n \cdot L \cdot k$ LSH to generate profile vectors for the image. Then the user invokes Share algorithm to share the secret key and performs $n \cdot L$ PRFs to generate Tag, Finally, the user performs $n \cdot L$ PRFs and $n \cdot L$ symmetric encryption to generate Piece∗ . To generate the query, the user performs $n \cdot L \cdot k$ LSH to generate profile vectors for the query image and then performs $n \cdot L$ PRFs to generate Tag. In the process of retrieval, the user performs $nLl \cdot (d +$ 1) PRFs to locate buckets and performs $nLl \cdot (d + 1)$ comparisons to compare contents in the buckets with tags. In the process of image recovery, the user performs m PRFs to generate keys for decrypting encrypted pieces, performs m symmetric decryption to recover pieces of the secret key, invokes Reconst to reconstruct the secret key, and finally performs symmetric decryption algorithm to decrypt the encrypted image.

From Table 2, we could see that our scheme is more efficient in retrieval, but more complex in image processing

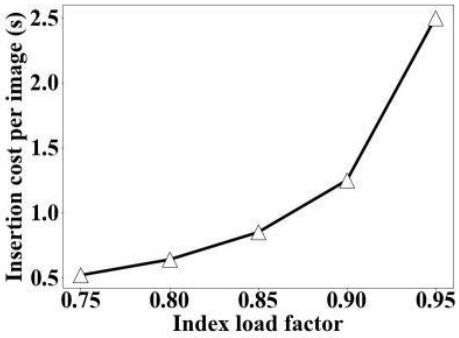


***FIGURE 3. Insertion cost.***

and image recovery compared with [5]. That's because in our scheme the key used for decrypting image is reconstructed by the user himself and in order to help the user recover the key, the image owner preprocess the key using the secret sharing techniques. And this also reduces the communication overhead between the users and the image owners. In [5], the server sends encrypted retrieval results to the image owner, and then image owner returns to the user the decrypted image. However, in our scheme, the users have no need to communicate with the image owner.

## VII. PERFORMANCE EVALUATION

We use Python to implement the prototype of our scheme. We deploy the prototype on a PC with Intel Core i7 3.4 GHz CPU and 8 GB RAM.

We use the computer vision library Opencv3 to process images and the OpenSSL library to achieve symmetric encryption and PRFs. The feature extraction algorithm is implemented using Oriented FAST and Rotated BRIEF (ORB)

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[11].The extended locality-sensitive hashing is implemented using random bits sampling based eLSH. We conduct our experiments on the UK Bench database [27] to test retrieval accuracy and system performance. Each group in the UK Bench database contains 4 images. The images in the same group capture the same object under different angles and illuminations. Therefore we consider images in a group as similar images. From the database, we randomly choose 3,000 images to build the secure index. We evaluate our system from the following aspects: image processing cost, query overhead, and retrieval accuracy. And all of the experimental results are the average of 100 operations.

**A. IMAGE PROCESSING COST** The parameters of the experiments are n = 120, t = 10, eLSH arguements (k, L) = (30, 80), and we test the computation cost of uploading one image. The experimental results show that in the process of image processing, it takes 0.003s to share the secret key, 0.056sto generate profile vectors, 0.081s to generate tags and encrypted pieces.

**B. QUERY COST** Whether a query is for retrieval, insertion, or deletion, the bandwidth is constant with respect to n × L tags in Tag. The parameter of the experiments are l × w = 30 million,

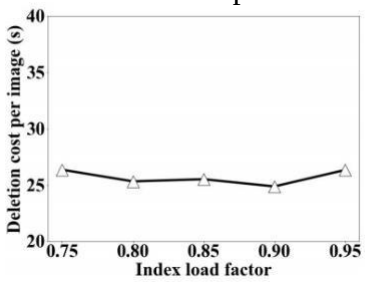


*FIGURE 4. Deletion cost*

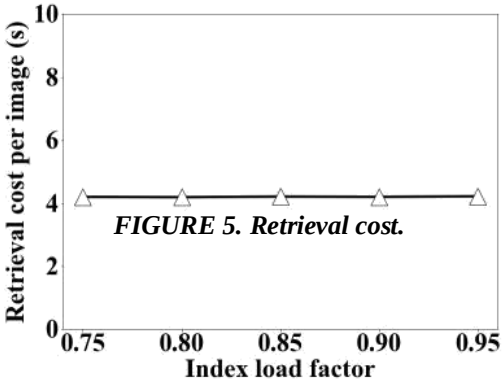


*FIGURE 5. Retrieval cost.*

*FIGURE 5. Retrieval cost.*

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probe value d = 3, n = 120, (k, L) = (30, 80). We test tag insertion cost for uploading 1 image, tag deletion cost for removing 1 image, and retrieval cost for querying 1 image respectively. • Insertion cost. Tags insertion may cause collisions in cuckoo hashing and further incur kick-away operations. As the index load factor $\tau$ grows, cuckoo kick-away operations occur more frequently which results in the growth of time cost, as shown in Fig.3. • Deletion cost. After receiving the deletion query from the user, the SS generates $n \times L$ trapdoors, accesses to $n \times L \times (d+1)$ buckets, and finally empties $n \times L$ buckets related to the query. As shown in Fig.4, the deletion cost is nearly constant under different $\tau$ . • Retrieval cost. Same as the tags deletion, after receiving the retrieval query, the SS generates $n \times L$ trapdoors. Then SS accesses $n \times L \times (d + 1)$ buckets in the cuckoo hashing, and filters contents in these buckets. As shown in Fig.5, the time cost under different $\tau$ is constant.

**C. RETRIEVAL ACCURACY**

Retrieval accuracy is affected by threshold value m and eLSH arguments (k, L). From Fig. 6, 7, 8, and 9, we could observe the influence of threshold value on the retrieval accuracy and the retrieval recall in our scheme. The growth of the threshold value causes the standard for measuring image similarity to become stricter, and leads to better retrieval accuracy and lower retrieval recall. Fig. 6 and 7 demonstrate the impact of L on retrieval accuracy and retrieval recall of our scheme, while Fig. 8 and 9 demonstrate the impact of k. The growth of L increases the retrieval recall and reduce the retrieval accuracy, while the increase of k leads to the increase of retrieval accuracy and the decrease of retrieval recall. The impact results of L and k are consistent with the characteristics of eLSH described in section III-A.

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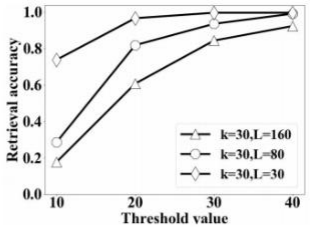


**FIGURE 6.** Accuracy for different *L*.

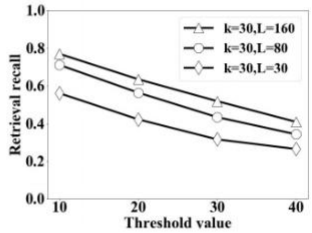


**FIGURE 7.** Recall for different *L*.

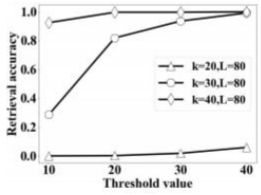


**FIGURE 8.** Accuracy for different *k*.

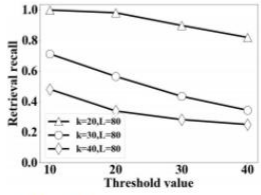


**FIGURE 9.** Recall for different *k*.

## VIII. CONCLUSION

In this paper, we proposed and implemented a privacy preserving content-based image retrieval and sharing scheme, which can be used for friend recommendation in social multimedia applications. We measured image similarity through image visual features. We used eLSH to reduce the dimensionality of visual features and realize similarity search on visual features.

We designed the index based on cuckoo hashing to speed up the similarity search. Based on secret sharing, we allowed the user to query and recover images on his own, which eliminates key management overhead

and access control overhead compared with other schemes. Finally, we implemented a prototype to evaluate the efficiency of our proposed scheme. The results showed that our scheme achieves practical performance under the UK Bench database.

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