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A Secure Rotation Invariant LBP Feature Computation in Cloud Environment

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Abstract: In the era of big data, outsourcing massive data to a remote cloud server is a promising approach. Outsourcing storage and computation services can reduce storage costs and computational burdens. However, public cloud storage brings about new privacy and security concerns since the cloud servers can be shared by multiple users. Privacy-preserving feature extraction techniques are an effective solution to this issue. Because the Rotation Invariant Local Binary Pattern (RILBP) has been widely used in various image processing fields, we propose a new privacy-preserving outsourcing computation of RILBP over encrypted images in this paper (called PPRILBP). To protect image content, original images are encrypted using block scrambling, pixel circular shift, and pixel diffusion when uploaded to the cloud server. It is proved that RILBP features remain unchanged before and after encryption. Moreover, the server can directly extract RILBP features from encrypted images. Analyses and experiments confirm that the proposed scheme is secure and effective, and outperforms previous secure LBP feature computing methods.

Keywords: Privacy-preserving; rotation invariant local binary pattern; cloud computing; image encryption

1 Introduction

With the rapid development of new information techniques such as big data, cloud computing, and the Internet of Things, users and companies are more willing to store their massive multimedia data on remote cloud servers. Cloud storage services have many advantages, including accessibility, convenience, and low storage expenditure, but massive multimedia data in the cloud servers contain some personal sensitive information needing to be protected. With the popularity of data outsourcing services, there is an increasing need for data security [1,2] and privacy protection in cloud computing. Privacy-preserving outsourcing protocol provides an effective way to cope with this problem [3].

So far, many privacy-preserving data outsourcing schemes have been developed. Previous privacy-preserving outsourcing works mainly focus on text documents. Song et al. [4] proposed practical cryptographic schemes supporting search on encrypted data by employing Boolean operators and phrase searches. Brinkman et al. [5] presented an efficient search method over encrypted data using secure multi-party computation in which XML elements are translated to polynomials. It prevented the server from revealing private content about the data or the query by splitting each polynomial into two parts. Boneh et al. [6] constructed a public key encryption mechanism that enables keyword search over encrypted email. User Alice provided a key to the gateway and tested whether the query word is a keyword in the email without revealing anything information about the email. Swaminathan et al. [7] designed a rank-ordered search framework over encrypted text documents. The scheme can return documents in the order of their relevance to the query term. Elmehdwi et al. proposed a secure k-nearest neighbor (kNN) protocol [8]. The secure kNN search scheme supports the kNN query, while the confidentiality of the data, the user's input query, and data access patterns. Analysis results indicate that the presented retrieval protocol on encrypted data is secure and efficient. However, common cloud servers in practice may be owned by multiple users rather than only one user. In [9], a privacy–preserving ranked multi-keyword search of encrypted data suitable for the multi-owner model was introduced. Recently, the study on privacy-preserving data outsourcing services has been drawn to multimedia data [10–14]. The Scale-Invariant Feature Transform (SIFT) is a popular method in the field of image processing. It is widely used in computer vision such as object recognition and tracking, and image matching. Hsu et al. [15] first proposed a privacy-preserving SIFT feature representation and extraction approach using the Paillier cryptosystem. It enables us to perform feature extraction in the encrypted domain. Hu et al. [16] focused on privacy–preserving computation outsourcing protocol for SIFT feature over massive encrypted image data and presented a secure SIFT feature extraction scheme. it achieved efficiency and security requirements simultaneously by preserving its key characteristics and designed two protocols for secure multiplication and comparison by randomly splitting original image data. To achieve good efficiency and security, Jiang et al. [17] proposed an effective privacy-preserving SIFT scheme for encrypted images. It devised leveled homomorphic encryption using a new encoding method, homomorphic comparison, division, and derivative encryption. Wang et al. [18] aimed at Speeded-up Robust Features (SURF) and proposed a privacy-preserving SURF computation scheme. it can preserve the distinctiveness and robustness of SURFs while enabling secure multiplication and comparison by leveraging somewhat homomorphic encryption (SHE) and single-instruction multiple-data (SIMD). Jiang et al. [19] first proposed a secure searchable image encryption algorithm for Block Truncation Coding (BTC) compressed images by encrypting the bit plane and two quantization levels of each subblock using the Henon chaotic map. Features based on BTC can be directly computed from encrypted images. Qin et al. [20] proposed a secure Harris feature extraction method for encrypted image retrieval that uses the improved Harris method, SURF, and the Bag of Words model to form the feature vectors. A privacy-preserving BTC feature extraction (PPBTC) is reported in [21]. First, all images are uploaded to the cloud after encryption. The privacy-preserving image encryption process consists of block permutation, pixel diffusion, and a bit-plane random shift. BTC features remain unchanged after encryption and the cloud server can directly extract BTC features from the encrypted images. Some analyses and experimental results demonstrate that the proposed privacy-preserving feature extraction scheme for BTC-compressed images is efficient and secure, and it can be used to secure image computation applications in cloud computing. A local sensitive hash algorithm was employed to produce the searchable index because of the wide application of image hash [22] in image retrieval. The chaotic encryption approach was used to protect the security of images and indexes. Sultana et al. [23] proposed privacy-preserving Local Binary Patterns computation outsourcing scheme that can extract LBP features from encrypted images, in which image encryption was applied only on the MSB (Most Significant Bit) plane of an image. All operations were performed on encrypted images without revealing any information to cloud servers. However, its image scrambling degree is not good. Aiming at secure online data storage services in the Industrial Internet of Things (IIoT), Xia et al. [24] proposed a secure image LBP feature computation scheme. It can directly extract LBP based features from the encrypted images without revealing the private content in the images.

Rotation invariant LBP (RILBP) is an excellent operator and has been widely applied in texture description. Privacy-preserving RILBP feature computation will gain wide application in secure cloud computing. To achieve direct RILBP-based feature representation and computation in the encrypted domain and preserve the privacy of images stored in remote servers, we proposed a privacy-preserving RILBP (PPRILBP) features computation outsourcing scheme in this paper.

The main contributions of this paper are as follows.

(1) This paper proposed a novel secure feature computation algorithm by combining block scrambling, pixel circular shift, and pixel diffusion. Since the feature extraction does not need to decrypt the encrypted data, the new encryption strategy enables direct calculation of RILBP features from encrypted images without revealing private information in images.
(2) The correctness of RILBP feature extraction in the encrypted domain has been proved. Meanwhile, only one server is needed for direct feature computation from encrypted images. Our PPRILBP scheme can find good applications in privacy-preserving image retrieval in cloud environment.
(3) Compared with existing secure LBP feature computation schemes, the new PPRILBP scheme has shown better robustness against common signal processing manipulations, including slight geometric attacks. It can achieve better retrieval accuracy.

The remainder of this paper is organized as follows. In Section 2, a rotation invariant local binary pattern is briefly introduced. Section 3 describes the proposed PPRILBP algorithm in detail. The experiment results and analyses are given in Section 4. Section 5 analyzes the correctness of feature extraction. Finally, the conclusion is made in Section 6.

2 Rotation Invariant Local Binary Pattern

The Local Binary Pattern (LBP) technique was first introduced by Ojala et al. [25]. As a well-defined texture descriptor, it has been widely used in various image processing fields such as image retrieval, image recognition, and image authentication. The original LBP operator assigns pixel value differences of each pixel with its 3×3 neighboring pixels as a binary number. The neighbor is marked as '1' if the corresponding pixel value is greater than the center pixel value and 0 otherwise.

The circular LBP is an extension of the basic LBP operator. It can deal with the texture description of different sizes. Let the notation (P, R) denote the neighbor set with P sampling points on a circle of radius R. The pixel values are bilinearly interpolated when the sampling point does not fall at integer coordinates. Given the center pixel (x_c, y_c) with pixel value I_c, the LBP number for the center pixel is calculated as follows.

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{P-1} s\left(I_p - I_c\right) 2^p \tag{1}$$

where I_p is the pixel value of the neighbor pixel $\left(x_p, y_p\right)$, and $s(x)$ is the sign function.

$$\begin{cases} x_p = x_c + R\cos\left(\dfrac{2\pi p}{P}\right) \\ y_p = y_c - R\sin\left(\dfrac{2\pi p}{P}\right) \end{cases} \tag{2}$$

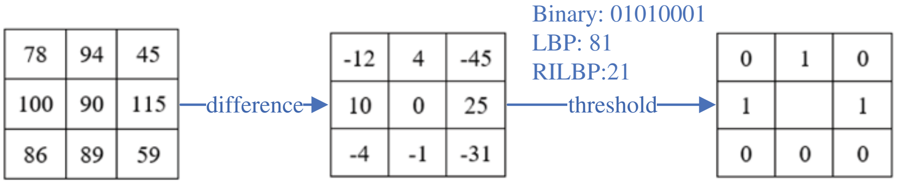
$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{3}$$

To remove the effect of rotation, the LBP operator is further extended to the so-called rotation invariant LBP operator, denoted as $LBP_{P,R}^{ri}$.

$$LBP_{P,R}^{ri} = \min\left\{ROR\left(LBP_{P,R}, i\right) \middle| i = 0, 1, \ldots, P-1\right\} \tag{4}$$

where $ROR(x, i)$ performs a right circular i-bit shift on each bit pattern and the function $\min(z)$ returns the minimum value of the array z.

For example, the linear permutation 11110000_2, 1110001_2, and 11000011_2 are different rotation versions of the same local pattern, and they all correspond to the same circular permutation with a minimum value 00001111_2. Let $P = 8$ and $R = 1$, Fig. 1 shows an example of the RILBP operator with a circular neighbor set $(8, 1)$



78	94	45
100	90	115
86	89	59

-12	4	-45
10	0	25
-4	-1	-31

0	1	0
1		1
0	0	0

Figure 1: The RILBP operator with a circular neighbor set (8, 1)

3 Proposed PPRILBP Scheme

In this section, the proposed secure outsourcing scheme for RILBP features is described in detail. All images will be encrypted using block scrambling, pixel circular shift, and pixel diffusion before uploaded into the remote server. The cloud server can directly compute the RILBP based features from encrypted images without decrypting them. The block diagram of the proposed method is illustrated in Fig. 2.

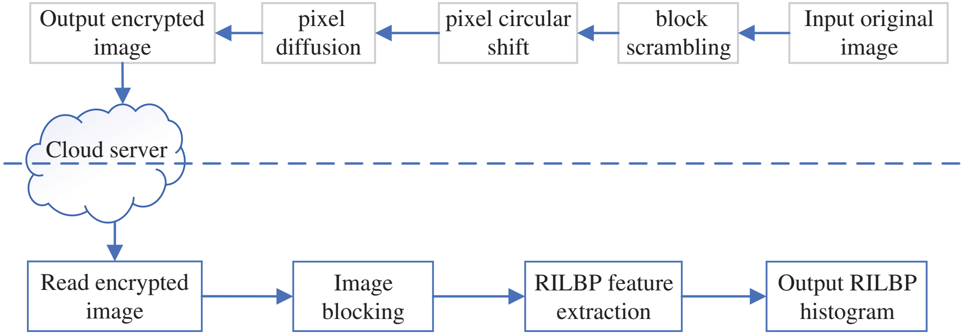


Figure 2: The block diagram of the proposed PPRILBP scheme

3.1 *Image Encryption*

In the image encryption phase, the original image is divided into 3 × 3 nonoverlapping blocks. Each subblock will undergo three processes: block scrambling, pixel circular shift, and pixel diffusion.

The secret key key_1 is used to produce pseudo-random permutations from the interval $[0, 1, \ldots, Nb - 1]$ during block scrambling, where Nb is the number of nonoverlapped blocks.

$$Nb = \frac{m \times n}{Bs \times Bs} = \frac{m \times n}{3 \times 3} \tag{5}$$

Then use secret key key_2 to generate a pseudo-random sequence ns for performing pixel shift on the neighbor pixels sequence $\mathcal{N}eb$. The pixel shift operation does not change the RILBP feature since the minimum of the LBP feature remains unchanged before and after pixel circular shifting. Finally, secret key key_3 is used to generate random sequences for performing pixel diffusion onto a circular shifted neighbor sequence $\mathcal{N}ec$ to further remove the correlation of the adjacent pixel. In order not to change the sign of the difference between the center pixel and the neighbor pixels, we adopt the following strategy,

$$\mathcal{N}ed\,(k) = \begin{cases} Inb2\,(\mathcal{N}ec\,(k) - xc + 1) & if\ \ \mathcal{N}ec\,(k) \geq xc \\ Inb1\,(\mathcal{N}ec\,(k) + 1) & else \end{cases}, \quad k = 0,\, 1,\, \ldots,\, P - 1 \tag{6}$$

where $\mathcal{N}ed$ is the sequence of diffused neighbor pixels, xc is the center pixel, ***Inb1*** *and* ***Inb2*** are the pseudo-random sequence less than xc and greater than or equal to xc, respectively.

The detailed steps for image encryption are described in Algorithm 1.

Algorithm 1: Image encryption

```
Input: original image $\mathcal{F}$ with size $m \times n$, secret key $key_1$, $key_2$ and $key_3$
Output: encrypted image $\mathcal{E}$
Initialization: block size $Bs = 3$, $P = 8$
Use $key_1$ to generate a pseudo-random permutation $\boldsymbol{Pb}$ within the interval $[0, 1, \ldots, Nb - 1]$.
for $i = 0$: $Nb - 1$
    $block'\,(Pb\,(i)) \leftarrow block\,(i)$
    Denote neighbor set as $\mathcal{N}eb$
```

(Continued)

```
    Denote the center pixel as $xc$.
    Use $key_2$ to generate a pseudo-random number $ns$ within $[0, 1, \ldots, Bs \times Bs - 1]$.
    Perform the right circular $ns$-pixel shift on the neighbor sequence $\mathcal{N}eb$ and generate $\mathcal{N}ec$.
    Use $key_3$ to generate pseudo-random permutations $\boldsymbol{Inb1}$ within the interval
     $[0, 1, \ldots, xc - 1]$ and $\boldsymbol{Inb2}$ within interval $[xc, xc + 1, \ldots, 255]$.
    for k $= 0 : P - 1$
        Update the neighbor pixels $\mathcal{N}ec$ using Eq. (6) and produce $\mathcal{N}ed$.
    end for
end for
```

The encrypted image $\mathcal{E}$ is produced when all image blocks are processed.

Image decryption is the inverse process of the encryption process. Given the same secret keys and image block size, users can recover the original images from encrypted images.

3.2 RILBP Feature Extraction From Encrypted Image

The proposed image encryption does not change the RILBP features of each block. The RILBP features can be directly computed in the encrypted domain without decryption. The main procedures of secure feature extraction are shown in Fig. 2, and a more detailed description of the proposed RILBP feature extraction method is illustrated in Algorithm 2.

```
Algorithm 2: RILBP feature extraction
Input: encrypted image $\mathcal{E}$ with size $m \times n$
Output: RILBP histogram feature $\mathcal{F}$
Initialization: block size $Bs = 3$, $P = 8$
    Divide the image $\mathcal{E}$ into nonoverlapped blocks.
    for $i = 0 : Nb - 1$
        Compute RILBP feature $\mathcal{F}(i)$ for the $i$th block using Eq. (4).
    end for
    Compute the RILBP histogram feature $\mathcal{F}$.
```

4 The Correctness of RILBP Histogram Features Extraction

Definition 1 (Identical), two sequences are identical if and only if they contain the same elements in the same order. For example, these two sequences $(5, 6, 23, 9, 3)$ and $(5, 6, 23, 9, 3)$ should be considered identical.

Definition 2 (Equivalent), two sequences are equivalent if and only if they are different permutations of all elements from the same set, where ordering does not matter. For instance, these two sequences $(3, 5, 6, 9, 23)$ and $(5, 6, 23, 9, 3)$ should be considered equivalent.

We consider the original image signal sequence $\mathcal{F}$. The signal is subdivided into blocks with a size of Bs. Let B_i be a subblock of the original image, i.e., $\mathcal{F} = (B_i)_0^{Nb-1}$. We denote $\mathbb{S}$ as the block scrambling transform,

$$\mathbb{S}(\mathcal{F}) = \mathcal{F}' \tag{7}$$

where $\mathcal{F}'$ is the scrambled image, $\mathcal{F}' = \left(B_i'\right)_0^{Nb-1}$.

Hence, we have

Theorem 1. The sequence $\mathcal{F}$ and corresponding scrambled sequence $\mathcal{F}'$ are equivalent, denoted as $\mathcal{F} \cong \mathcal{F}'$.

Proof. Since the block scrambling transforms $\mathbb{S}$ only changes the position of an image subblock, the two sequences $\mathcal{F}$ and $\mathcal{F}'$ contain the same image subblock except that only ordering of the subblock in the sequences is different. Therefore, the two sequences $\mathcal{F}$ and $\mathcal{F}'$ are equivalent according to Definition 2.

For any subblock $B' \in \mathcal{F}'$, the center pixel xc and the neighbor sequence $\mathcal{N}eb$ are got at first. The definition of the circular pixel shift operator $\mathbb{C}$ is as follows.

Definition 3. The circular pixel shift operator $\mathbb{C}(\mathcal{N}eb, x)$ performs right circular x-pixel shift on the neighbor sequence $\mathcal{N}eb$ and produces a new sequence $\mathcal{N}ec$,

$$\mathbb{C}(\mathcal{N}eb, x) = \mathcal{N}ec \tag{8}$$

The sequence $\mathcal{N}eb$ and its circular shifted sequence $\mathcal{N}ec$ are rotation invariant, denoted as $\mathcal{N}eb \overset{Ri}{=} \mathcal{N}ec$.

Denote the pixel diffusion strategy as $\mathbb{D}$, according to Eq. (6), we have

$$\mathbb{D}(\mathcal{N}ec) = \mathcal{N}ed \tag{9}$$

Besides, then the following lemma can be concluded.

Lemma 1. Pixel diffusion strategy $\mathbb{D}$ does not change the sign of the difference between the center pixel and the neighboring pixels, i.e., $sign(\mathcal{N}ec - xc) = sign(\mathcal{N}ed - xc)$.

Proof.

$$\begin{aligned}
&\forall k \in \{0, 1, \ldots, P-1\}\\
&if\, \mathcal{N}ec(k) - xc \geq 0\\
&\quad \mathcal{N}ed(k) - xc = Inb2(\mathcal{N}ec(k) - xc + 1) - xc\\
&\quad \because Inb2(\mathcal{N}ec(k) - xc + 1) \geq xc\\
&\quad \therefore \mathcal{N}ed(k) - xc \geq xc - xc = 0\\
&else\\
&\quad \mathcal{N}ed(k) - xc = Inb1(\mathcal{N}ec(k) + 1) - xc\\
&\quad \because Inb1(\mathcal{N}ec(k) + 1) < xc\\
&\quad \therefore \mathcal{N}ed(k) - xc < xc - xc = 0
\end{aligned}$$

Therefore, the sign of the difference between the center pixel and the neighbor pixels remains unchanged before and after pixel diffusion, i.e., $sign(\mathcal{N}ec - xc) = sign(\mathcal{N}ed - xc)$.

Let B'_c, B'_d be the circularly shifted subblock and the pixel diffused subblock of any subblock B', respectively. Let $LBP(\cdot)$, $RILBP(\cdot)$ be the LBP and RILBP operators, respectively. Let $\mathcal{E}$ be the encrypted image signal sequence. Then, we have

Theorem 2. $RILBP(\mathcal{F}') = RILBP(\mathcal{E})$.

Proof. $\forall B' \in \mathcal{F}', \forall B'_d \in \mathcal{E}$,

$\mathcal{N}eb$, $\mathcal{N}ec$, $\mathcal{N}ed$ are neighbor sequences derived from subblocks B', B'_c, B'_d, respectively.

According to Lemma 1, we have $sign(\mathcal{N}ec - xc) = sign(\mathcal{N}ed - xc)$.

So, $LBP\left(B'_c\right) = LBP\left(B'_d\right)$

$\because \mathcal{N}eb \overset{Ri}{=} \mathcal{N}ec$

$\therefore RILBP\left(B'\right) = RILBP\left(B'_d\right)$

Thus, $RILBP\left(\mathcal{F}'\right) = RILBP\left(\mathcal{E}\right)$ since B', B'_d are any subblocks of sequences $\mathcal{F}'$, $\mathcal{E}$, respectively.

Finally, the following theorem be proved

Theorem 3. The histogram of RILBP features computed from the original image and encrypted images are the same,

Proof.

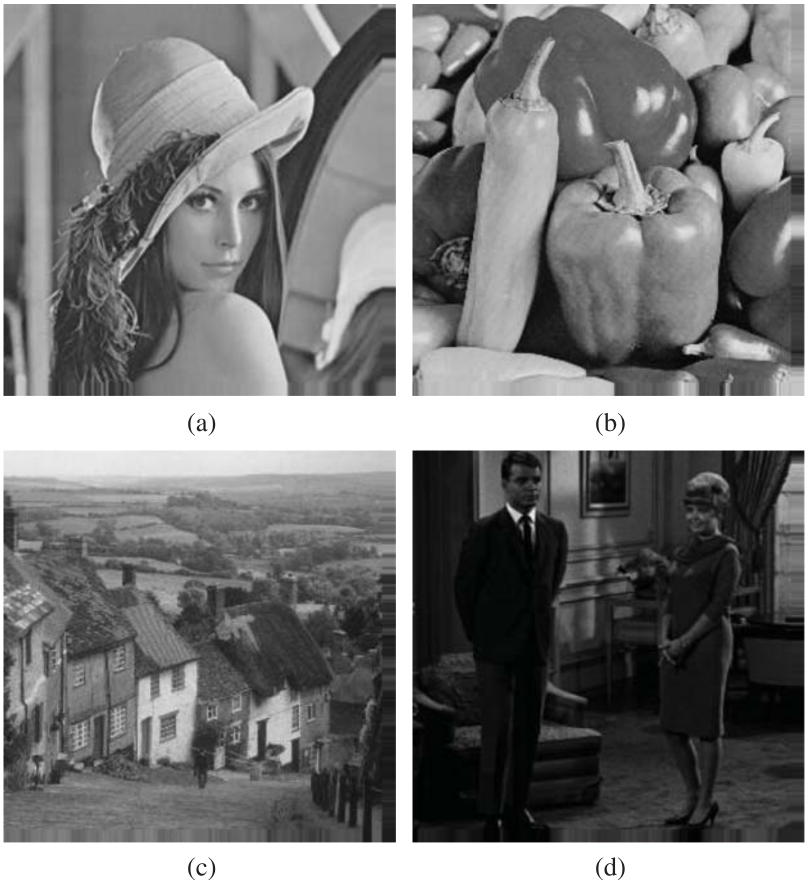
We have $\mathcal{F} \cong \mathcal{F}'$ according to Theorem 1.

So, $RILBP\left(\mathcal{F}\right) \cong RILBP\left(\mathcal{F}'\right)$

Also, because $RILBP\left(\mathcal{F}'\right) = RILBP\left(\mathcal{E}\right)$ according to Theorem 2.

We have $RILBP\left(\mathcal{F}\right) \cong RILBP\left(\mathcal{E}\right)$.

Since the histogram feature does not consider the ordering of elements, we can conclude that the same RILBP histogram features can be computed from the original image and encrypted image, respectively.



(a) (b)

(c) (d)

Figure 3: Original images (a) Lena (b) peppers (c) Goldhill (d) couple

5 Experimental Results and Analyses

The section provides some analyses and experiments to validate the security and effectiveness of the proposed PPRILBP outsourcing algorithm. The algorithm is conducted on the USC-SIPI Image Database. Fig. 3 shows some test images from the image dataset. In the experiments, we set $P = 8$ and $R = 1$. The generated encrypted images by our PPRILBP algorithm are illustrated in Fig. 4. According to Fig. 4, one cannot observe useful information from the encrypted image by human eyes.

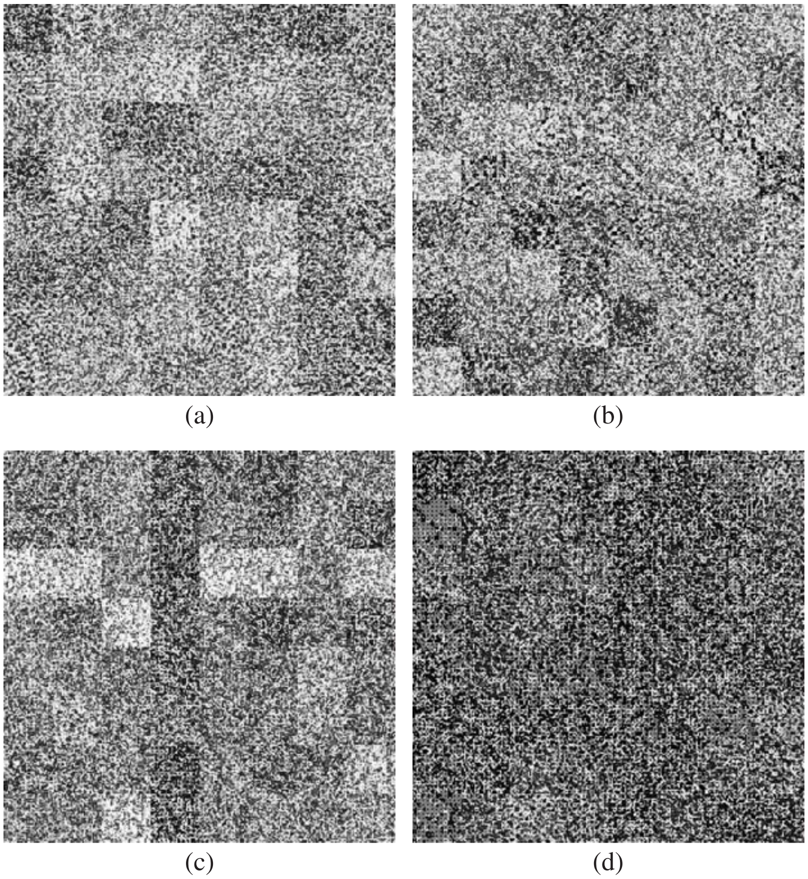


Figure 4: Encrypted images (a) Lena (b) peppers (c) Goldhill (d) couple

5.1 Security Analysis

In this section, the key space size is first investigated, which is the total number of different keys used in the encryption process. In the proposed PPRILBP algorithm, the secret key consists of three secret keys (*key1*, *key2*, and *key3*). If each secret key has a precision of 10^{-15} then there will be 15 + 15 + 15 = 45 uncertain digits of the secret key combination. This means that the complete key space for the proposed secure feature extraction reaches up to 10^{45}, i.e., our PPRILBP algorithm possesses an effective key length of $\log_2 \left\{10^{45}\right\} \approx 150$ bits. The key space of our algorithm is larger than that of the 128-bit encryption. Therefore, we can say that the proposed PPRILBP algorithm has a large enough key space and can resist all kinds of brute-force attacks.

Besides, a good image encryption scheme should be sensitive to the secret keys. In our scheme, the sensitivity to *key1*, *key2*, and *key3* is considered as 10^{-15}. To test the key sensitivity, the original image (taking the Lena image as an example) is first encrypted using secret keys ($key1 = 0.74$, $key2 = 0.79$, $key3 = 0.13$), and the resultant encrypted mage is shown in Fig. 5a. Fig. 5b is the decrypted Lena image using the correct key, and Figs. 5c–5e are the decrypted images using the wrong key, respectively. From Fig. 5, we can find that even a secret key set with a tiny change (10^{-15}) does not reveal any information on the plain-image. Therefore, the proposed scheme has a high key sensitivity.

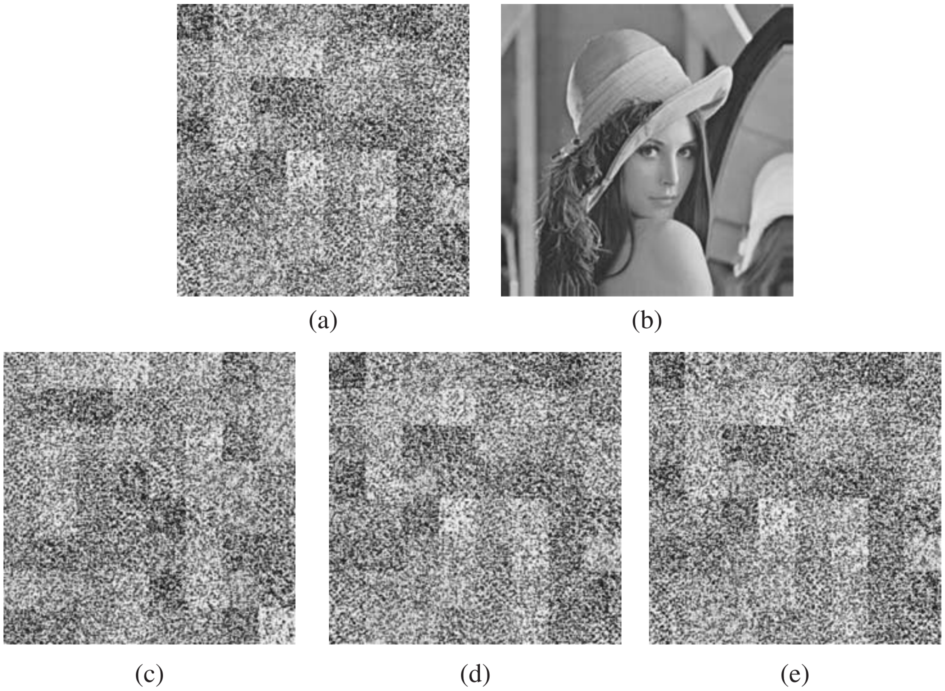
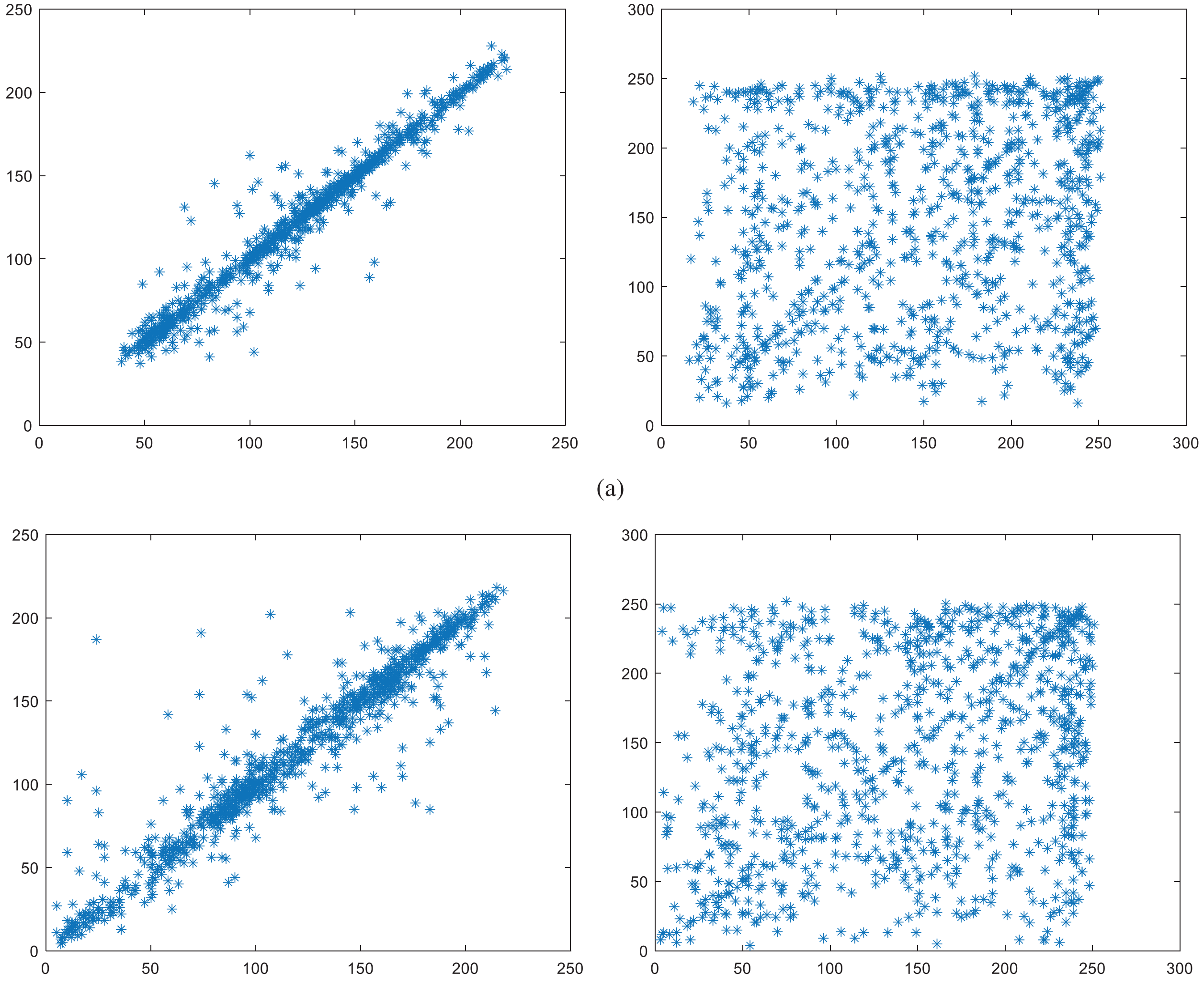

(a) (b) (c) (d) (e)

Figure 5: Key sensitivity test. (a) Encrypted image using key ($key1 = 0.74$, $key2 = 0.79$, $key3 = 0.13$). (b) Decrypted image using key ($key1 = 0.74$, $key2 = 0.79$, $key3 = 0.13$). (c) Decrypted image using key ($key1 = 0.74 + 10^{-15}$, $key2 = 0.79$, $key3 = 0.13$). (d) Decrypted image using key ($key1 = 0.74$, $key2 = 0.79 + 10^{-15}$, $key3 = 0.13$). (e) Decrypted image using key ($key1 = 0.74$, $key2 = 0.79$, $key3 = 0.13 + 10^{-15}$)

5.2 Adjacent Pixels Correlation Analysis

An efficient image encryption system should generate encrypted images with low correlation in the adjacent pixels. The distribution of the adjacent pixels in the original image and its corresponding encrypted image provide an effective visual measure way of the correlation of adjacent pixels. Fig. 6 shows the correlation distribution of two horizontally adjacent pixels of the original image and encrypted image generated by our proposed scheme. The left column and the right column are the correlation distribution of the original image and its corresponding encrypted image, respectively. We can see that the correlation between adjacent pixels in the encrypted image is diffused effectively. The encrypted images produced by our proposed scheme have a weaker correlation than their original images. Thus, the new image encryption algorithm can almost eliminate the correlation of pixels.



(a)

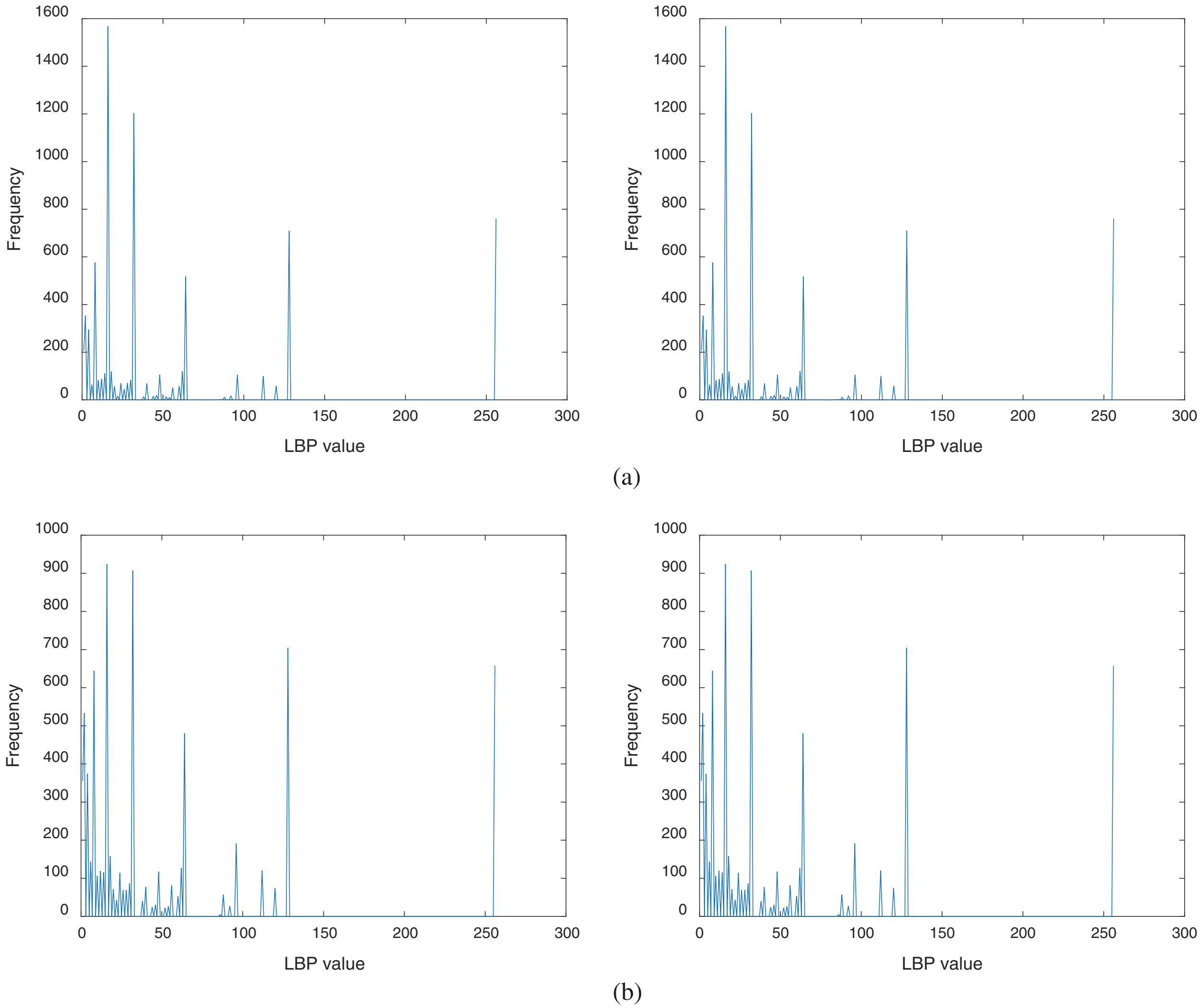
(b)

Figure 6: Correlation of two horizontally adjacent pixels. Left column: original images, right column: encrypted images (a) Lena (b) peppers

5.3 Direct PPRILBP Feature Extraction on Encrypted Data

We extract the features from original images and encrypted images for evaluating the accessibility of feature computation. The extracted RILBP features are shown in Fig. 7. The features from the original image and encrypted image are illustrated in the left column and the right column, respectively. It is not hard to notice that the image encryption scheme extracts the same PPRILBP features from the original image and encrypted images. So, the proposed

PPRILBP scheme can achieve a high successful retrieval rate when used to image retrieval in cloud computing.



(a)

(b)

Figure 7: RILBP feature extraction before and after image encryption. Left column: features extracted from original images, right column: features extracted from encrypted images. (a) Lena (b) peppers

Moreover, we further calculate the similarities between different images for homomorphic evaluation. Pearson's correlation coefficient is employed to evaluate feature similarity, where $E(X)$ denotes the mathematical expectation.

$$sim = \frac{E(H_1 H_2) - E(H_1)E(H_2)}{\sqrt{E\left({H_1}^2\right) - E^2(H_1)}\sqrt{E\left({H_2}^2\right) - E^2(H_2)}} \tag{10}$$

The corresponding test results are listed in Tabs. 1 and 2, respectively. It can be found that feature similarity remains unchanged before and after encryption by observing Tabs. 1 and 2. This indicates that the feature vector extracted by our PPRILBP scheme is homomorphic.

Table 1: Similarities of different original images in Fig. 3

	Fig. 3a	Fig. 3b	Fig. 3c	Fig. 3d
Fig. 3a	1	−0.0393	−0.0406	−0.0326
Fig. 3b	−0.0393	1	−0.0600	−0.0476
Fig. 3c	−0.0406	−0.0600	1	−0.0497
Fig. 3d	−0.0326	−0.0476	−0.0497	1

Table 2: Similarities of different encrypted images in Fig. 4

	Fig. 4a	Fig. 4b	Fig. 4c	Fig. 4d
Fig. 4a	1	−0.0393	−0.0406	−0.0326
Fig. 4b	−0.0393	1	−0.0600	−0.0476
Fig. 4c	−0.0406	−0.0600	1	−0.0497
Fig. 4d	−0.0326	−0.0476	−0.0497	1

5.4 Case Study on Privacy-Preserving Image Retrieval

As an excellent texture descriptor, LBP has been successfully employed for feature extraction in image retrieval due to its high discriminating ability. In experiments. We apply the proposed PPRIBP algorithm and Xia et al. [24] scheme to search images under the USC-SIPI Image Database. General evaluation metrics recall and precision is employed to evaluate image matching. Fig. 8 shows the performance of the proposed method and Xia et al. [24] scheme. From Fig. 8, we can notice that the performance of the proposed PPRILBP method is better than that by existing work when recall is not more than 0.5. Since that the higher precision with low recall is of more practical significance for image retrieval application, it can be concluded that our PPRILBP outperforms the existing secure LBP feature extraction scheme [24].

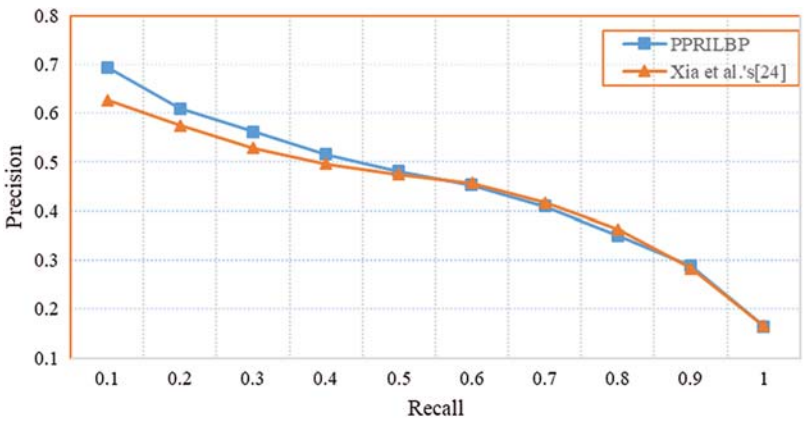


Figure 8: Precision-recall curves of different retrieval methods

6 Conclusion

Rotation Invariant Local Binary Pattern is a popular texture descriptor in computer vision applications. We propose a secure outsourcing scheme of RILBP feature computation. The image encryption using block scrambling, pixel circular shift, and pixel diffusion does not change the RILBP feature of each block. So, the same features can be computed from both the original images and encrypted images. Its security and performance are analyzed and evaluated. Experiments and analysis show that our scheme can directly extract features from encrypted data while preserving privacy and has better retrieval performance than the existing privacy-preserving LBP feature extraction method.

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