

SECURITY EVALUATION OF COMPRESSIBLE IMAGE ENCRYPTION FOR PRIVACY-PRESERVING IMAGE CLASSIFICATION AGAINST CIPHERTEXT-ONLY ATTACKS

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Abstract:

The security of learnable image encryption schemes for image classification using deep neural networks against several attacks has been discussed. On the other hand, block scrambling image encryption using the vision transformer has been proposed, which applies to lossless compression methods such as JPEG standard by dividing an image into permuted blocks. Although robustness of the block scrambling image encryption against jigsaw puzzle solver attacks that utilize a correlation among the blocks has been evaluated under the condition of a large number of encrypted blocks, the security of encrypted images with a small number of blocks has never been evaluated. In this paper, the security of the block scrambling image encryption against ciphertext-only attacks is evaluated by using jigsaw puzzle solver attacks.

Keywords:

Image Encryption; Ciphertext-only Attack; Jigsaw Puzzle Solver; Security;

1 Introduction

In recent years, the rapid development of deep neural networks (DNNs) enables us to implement speech recognition and image classification with high accuracy[1]. With the rapid growth of DNNs, cloud services like Microsoft Azure and Amazon Web Services are becoming popular instead of using local computing servers owing to the ease of use. When image classification is performed by cloud computing, security is a concern because the original image must be transmitted to the cloud side. To protect the security of images for classification under the cloud services, privacy preserving DNNs have been proposed, which encrypt ones before transmission. Although several image encryption schemes for privacy preserving DNNs have been proposed[2], [3], [4], [5], [6], some attacks success-

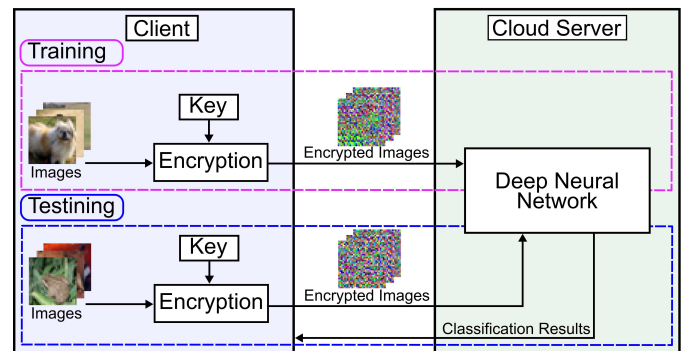


FIGURE 1. Image classification using deep neural networks

fully restore the visual information of the encrypted images[7], [8], [9]. Therefore, it is essential to use the image encryption method, which can be applied to privacy preserving DNNs and robust against various attacks.

On the other hand, a block scrambling image encryption (BE), which applies to lossless compression methods like JPEG standard, is proposed to generate visually protected images[10]. The BE is first carried out by dividing an image into blocks; then block-based encryption such as permutation is applied to each block. In this scheme, 8×8 or 16×16 -block should be used to avoid decreasing compression performance. It has been known that the use of block scrambling enhances robustness against several attacks, but significantly decreases the performance of DNNs. Owing to the vision transformer (ViT)[11], a model for image classification based on the transformer architecture, the BE can be used for privacy-preserving DNNs without a decrease in the performance of DNNs[12].

Robustness of the BE against jigsaw puzzle solver attacks (JPS-attack) that utilize a correlation among the blocks has

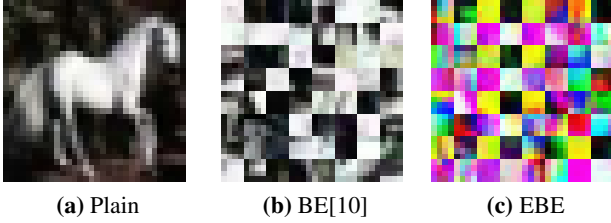


FIGURE 2. Example of compressible encrypted images

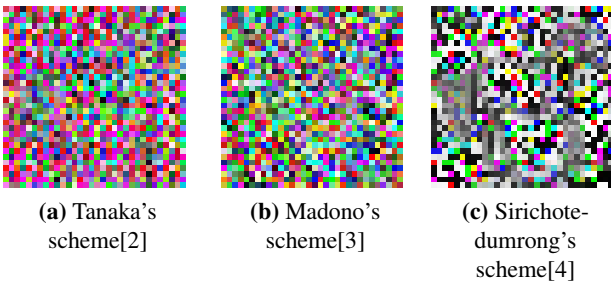


FIGURE 3. Example of non-compressible encrypted images

been evaluated[13]. It shows that robustness of the BE against the JPS-attack is enhanced, when encrypted images include a large number of small blocks. If the resolution of images for image classification is low (like 32×32 pixels), the total number of blocks in the encrypted image is small. Therefore, the security of the BE under the condition of a small number of encrypted blocks should be evaluated. In this paper, the security of the BE against ciphertext-only attacks is evaluated by using the CIFAR-10 dataset which includes color images of 32×32 pixels.

2 Preparation

2.1 Image Encryption for Deep Learning

Some image encryption schemes have been proposed to apply image classification using deep neural networks as illustrated in Fig.1. There are two types of learnable image encryption for deep learning. One is compressible and other is non-compressible image encryption as illustrated in Fig.2 and 3. Compressible image encryption schemes are carried out by dividing an image into encrypted blocks to apply the JPEG standard. On the other, non-compressible image encryption schemes are carried out pixel by pixel. In this paper, we focus on the security of compressible image encryption.

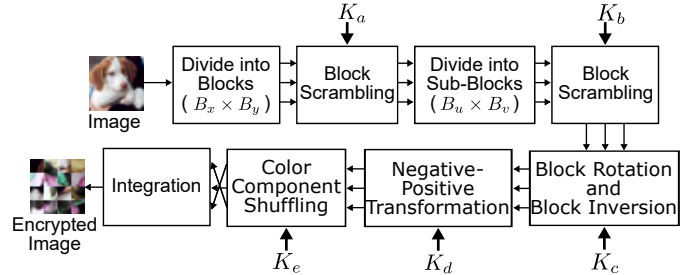


FIGURE 4. Extended block scrambling image encryption

2.2 Block Scrambling Image Encryption

In a block scrambling image encryption (BE)[10], an image with $X \times Y$ pixels is first divided into non-overlapped blocks with $B_x \times B_y$. Next, four steps are applied to the divided image as described below.

- Step 1: Shuffle the position of each divided block randomly using a random integer which is generated by a secret key K_1 . Note that all color components in each block are commonly permuted based on K_1 .
- Step 2: Rotate and flip each block by using a secret key K_2 , where K_2 is commonly used for all color components as step 1. Namely, each divided block is rotated by 0, 90, 180, and 270 degrees and inverted horizontally and vertically according to K_2 .
- Step 3: Implement negative-positive transformation on each block by using a secret key K_3 , which is commonly used for all color components. For instance, a pixel p , which is 8-bit pixel values, is transformed to p' by

$$p' = \begin{cases} p & (r(i) = 0) \\ p \oplus (2^8 - 1) & (r(i) = 1) \end{cases}, \quad (1)$$

where $r(i)$ is a random binary integer generated by K_3 . In this paper, the value of occurrence probability $P(r(i))$ is fixed to 0.5 to invert bits randomly.

- Step 4: Apply color components shuffling to each block by using a secret key K_4 .

An example of an encrypted image ($B_x = B_y = 4$) is illustrated in Fig.2(b); Fig.2(a) shows the original one with 32×32 pixels.

2.3 Extended Block Scrambling Image Encryption

To enhance robustness against several attacks, an extended block scrambling image encryption (EBE) was proposed. In

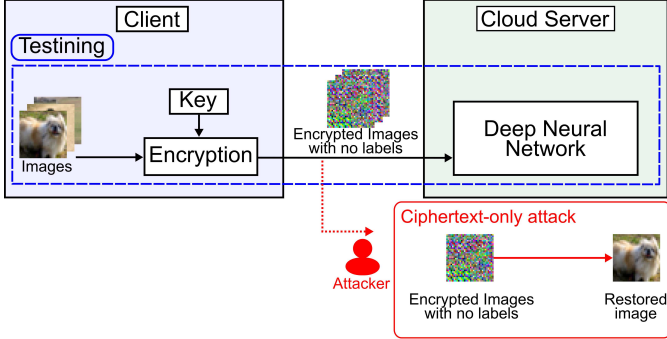


FIGURE 5. Scenario of restoring visual information from encrypted images with no labels using the ciphertext-only attack

this scheme, block scrambling is carried out two times as illustrated in Fig.4. The procedure of the extended block scrambling image encryption is described below.

- Step 1: Permute randomly the divided blocks with $B_x \times B_y$ pixels using a random integer generated by a secret key K_a , where K_a is commonly used for all color components.
- Step 2: Split each divided block to generate sub-block, each with $B_s \times B_t$ pixels, and permute randomly the sub-blocks within the block using a random integer generated by a secret key K_b .
- Step 3: Rotate and invert randomly each sub-block by using a random integer generated by a key K_c .
- Step 4: Apply negative-positive transformation to each sub-block by using a random binary integer generated by a key K_d in accordance with Eq.(1).
- Step 5: Shuffle three color components in each sub-block by using an integer randomly selected from six integers by a key K_e .

In this scheme, although the keys K_a and K_e are commonly used for all color components, K_b , K_c and K_d can be used independently. Figure 2(c) shows the example of image generated by using the EBE ($B_x = B_y = 8$, $B_s = B_t = 4$).

3 Attacks for Image Encryption

Several attacks for learnable image encryption have been proposed to restore visual information from encrypted images. In this paper, we evaluate robustness of encrypted images

TABLE 1. Key space of the BE and EBE

Encryption scheme	Key space
BE	$n! \cdot 8^n \cdot 2^n \cdot 6^n$
EBE(common key)	$n! \cdot n_s! \cdot 8^{n_s} \cdot 2^{n_s} \cdot 6^{n_s}$
EBE(independent key)	$n! \cdot 3n_s! \cdot 8^{3n_s} \cdot 2^{3n_s}$

against ciphertext-only attacks (COAs). As shown in Fig.5, the use of COAs enables us to restore visual information by using the encrypted image without its label. Brute-force attack, feature reconstruction attack and jigsaw puzzle solver attack are effective to reconstruct encrypted images.

3.1 Brute-force Attack

Robustness against brute-force attack is discussed in terms of key space, which depends on the resolution of an encrypted image, encryption steps and its block size. It has been known that the encryption scheme is robust against the brute-force attack when the key space is larger than 2^{256} [14]. In the BE, the number of encrypted blocks n is given by

$$n = \lfloor \frac{X}{B_x} \rfloor \times \lfloor \frac{Y}{B_y} \rfloor, \quad (2)$$

where $\lfloor \cdot \rfloor$ is a function that rounds down to the nearest integer.

On the other hand, the number of sub-blocks in the divided block by using the EBE is represented by

$$n_s = \lfloor \frac{B_x}{B_s} \rfloor \times \lfloor \frac{B_y}{B_t} \rfloor. \quad (3)$$

Table 1 shows the key space of the BE and EBE. In the BE and EBE, the use of small block size enhances robustness against brute-force attack because the key space increases with the number of divided blocks.

3.2 Feature Reconstruction Attack

A feature reconstruction attack (FR-Attack), which uses the edge information on images, is proposed to restore visual information of encrypted ones as described in Algorithm 1[15]. It has been known that permuting pixels or blocks in the encrypted image enhances robustness against the FR-attack.

3.3 Jigsaw Puzzle Solver Attack

A jigsaw puzzle solver attack (JPS-attack) is performed by regarding the permuted blocks as pieces of a jigsaw puzzle.

Algorithm 1 FR-attack[15]

Require: Encrypted input image I_e of size $X \times Y$;
number of bits L ; leading bit $b \in \{0, 1\}$

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1: for  $p = (u, v) \in I_e$  do
2:   for  $c \in R, G, B$  do
3:     if  $\lfloor p_c / (2^L - 1) \rfloor \neq b$  then
4:        $p_c \leftarrow p_c \oplus (2^L - 1)$ 
5:     end if
6:   end for
7: end for
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TABLE 2. Robustness against the FR-attack and JPS-attack

Key	Encryption scheme					
	BE		EBE		EBE	
	common	common	common	independent	independent	independent
Block size $B_x = B_y$ ($B_s = B_t$)	16	8	32 (16)	16 (8)	32 (16)	16 (8)
Number of blocks	4	16	4	16	4	16
FR-Attack (SSIM value)	0.05	0.04	0.05	0.04	0.06	0.05
JPS-Attack (L_c value)	0.94	0.51	0.94	0.56	0.25	0.06

Compared to the FR-attack, the JPS-attack is effective of restoring visual information even when encrypted images include permuted blocks. It is known that the use of a smaller block size and a large number of blocks in the encrypted image makes JPS-attack difficult to restore visual information[16].

4 Security Evaluation

4.1 Experimental Conditions

In this section, the security of the BE and EBE was discussed by using the FR-attack and JPS-attack. We employed 30 images randomly chosen from the CIFAR-10 dataset, which includes 32×32 color images. Each image was encrypted separately by using the BE and EBE and then the security of the encrypted image was evaluated.

Robustness against the FR-attack was evaluated by using structural similarity (SSIM) values for the original image and restored one. In experiments, the average SSIM value for the 30 images was calculated. Since SSIM values decrease dramatically due to the block scrambling, largest component

$L_c \in [0, 1]$, which means the ratio of the correct pairwise adjacencies, was utilized to evaluate the assembled image by using the JPS-attack[17]. In this measure, the larger value of L_c is, the more visual information is restored. The extended jigsaw puzzle solver[13] is utilized as JPS-attack. Robustness against the JPS-attack is evaluated by using 20 different encrypted images, which were generated from one ordinary image by using different keys. After assembling 20 encrypted images by the JPS-attack, the image which has the highest L_c was selected for evaluation. We performed this procedure for each encrypted image independently and calculated the average L_c for the 30 images.

4.2 Experimental Results

Table 2 shows the result of security evaluation against the FR-attack and JPS-attack. Although the large block size like 16×16 was used for encryption, the BE and EBE are robust against FR-attack. On the other hand, encrypted images with the BE and EBE using the common key are not robust even when the small block size (8×8) is used for encryption as illustrated in Table 3, where Fig.2(a) is the original one. However, it was confirmed that the EBE using the independently key is robust against the JPS-attack and FR-attack.

5 Conclusion

In this paper, we evaluated the security of compressible image encryption for privacy-preserving image classification against ciphertext-only attacks. In experiments, robustness of block scrambling image encryption (BE) and extended block scrambling image encryption (EBE) was evaluated by using the feature reconstruction attack (FR-Attack) and jigsaw puzzle solver attack (JPS-attack) as ciphertext-only attacks. Experimental results show that the jigsaw solver can restore visual information from encrypted images with the BE, even when the block size for encryption is small (8×8). On the other hand, it was confirmed that encrypted images using the EBE are robust against several attacks, even when large block size (16×16) is utilized.

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TABLE 3. Example of encrypted and restored images by using the FR-attack and JPS-attack

Encryption scheme	BE		EBE		EBE	
Key	common		common		independent	
Block size $B_x = B_y$ ($B_s = B_t$)	16	8	32 (16)	16 (8)	32 (16)	16 (8)
Encrypted image						
FR-Attack						
JPS-Attack						

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