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Identification of Multi-Dimensional Electromagnetic Information Leakage Using CNN

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ABSTRACT The unintentional electromagnetic (EM) radiation from electronic information equipment will cause the leakage of information. EM information leakage identification is an important research area of EM information security. Previous studies only focused on a particular type of information leakage, ignoring that there are multiple types of information contained in the leaked EM signal. This paper presents a multi-dimensional information leakage model for the first time, which reveals the multiple information leakage risks in an unintentional EM radiation. The EM information leakage of computer monitors is taken as an example to verify the model. Furthermore, a Convolutional Neural Network (CNN) based multi-dimensional information identification method is proposed. This novel method designed a unified neural network architecture to identify multiple information leaked by the same EM radiation from the monitor. It overcomes the limitation of available identification methods that need to definite leakage characteristics for each type of information leakage. The effectiveness of the method is validated by contrast experiments.

INDEX TERMS Unintentional electromagnetic radiation, information leakage, multi-dimensional information, information identification, convolutional neural network.

I. INTRODUCTION

Electromagnetic (EM) radiation can be generated in the process of operating an electronic device according to the principle of electromagnetism. For electronic devices, the radiation is unintentional and inevitable. It has been proved that EM radiation can cause the information leakage from the electronic device. EM information leakage is imperceptible, often is ignored. Since the first reported experiment of eavesdropping the image information from the EM emanation of video display units [1], researchers have captured and reconstructed image information leaked from cathode ray tube (CRT) [2]–[4], liquid crystal display (LCD) [5]–[7], laptop [8]–[10]. Other electronic devices or components, such as keyboard [11], power line [12], smart card [13] and microprocessor [14], have also been shown to leak information via EM radiation.

Analysis and identification of EM information leakage has become an important branch of information security research [15]. So far, the research about the identification or recognition for EM information leakage mainly focuses on two types of objects: leaked information and leakage source information. Leaked information recognition is to obtain the information being processed in electronic devices with the EM radiation. The research in this aspect includes: eavesdropping the image information being displayed from computer monitors [6] or connecting wires [12], intercepting the input information typed with keyboards [11], cracking the secret key of the encryption chip [16] and so on. Leakage source information identification is to locate where EM information leakage occurs [17] or identify the electronic device by its EM characteristics [18].

In fact, the above two kinds of information leakage often occur at the same time, and are contained in the same EM leakage signal. It means that there are many different types of information hidden in a single EM signal emitted by electronic devices unintentionally, which is almost overlooked. Previous research has tended to focus on just one type of information and identify it by analyzing its unique characteristics.

In this work, we propose a novel model to represent multi-dimensional information in unintentional EM leakage.

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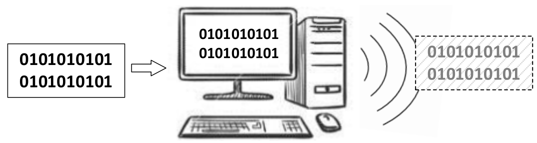


FIGURE 1. Information leaked by equipment.

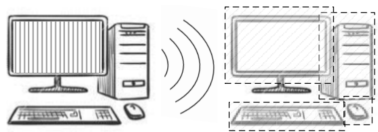


FIGURE 2. Information of equipment.

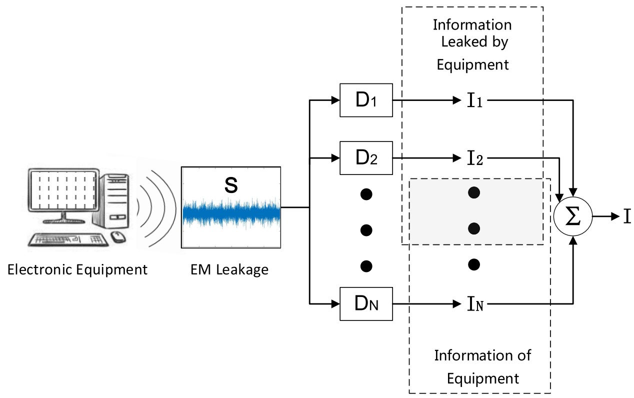


FIGURE 3. Model of multi-dimensional information for EM leakage.

The model attempts to unify the problems of EM information leakage into a theoretical framework. Furthermore, we present a new method to identify the leaked multi-dimensional information. Different from the previous works of one identification method for one type of leakage information, our method uses a uniform Convolutional Neural Network (CNN) [19] architecture to identify multiple leakage information. We specially designed one-dimensional (1D) convolution kernels and a suitable network structure to adapt the characteristics of EM leakage signals. It can be proved that the performance of our CNN is superior to the popular CNNs in EM information leakage recognition.

The rest of the paper is organized as follows: Section II describes the model of multi-dimensional information for EM leakage with an instance of the computer monitor. In Section III, we review the related works and introduce the proposed method. In Section IV, the experiment is described in detail. Section V discusses the results and some ideas about our work. Finally, we will summarize the conclusion and present the future work in Section VI.

II. MULTI-DIMENSIONAL INFORMATION OF EM LEAKAGE

A. TYPES OF MULTI-DIMENSIONAL INFORMATION FROM EM LEAKAGE

The EM signals leaked by electronic equipment contain various information threatening the information security. In our opinion, the information hidden in EM signals can be divided into two types: information leaked by equipment and information of equipment.

Information leaked by equipment is the data being processed in the electronic equipment. For examples, the image displayed in monitor, and the cryptograph information calculated by encryption device. When the data being processed in the equipment, the information about the data leaks out in the form of EM waves from the equipment, as shown in Fig.1. In this process, the equipment is looked like the medium for EM information leakage.

Information of equipment is the characteristics information of the electronic equipment itself, as illustrated in Fig.2. For examples, electronic performance, operating parameters, location, and EM fingerprints. Information leaked by equipment is directly about data security. Information of equipment, by contrast, is indirectly affecting data security by threatening device security.

It should be noted that the two types are not mutually exclusive, and some of the leaked information has characteristics of both types. For instance, the resolution of an image when it is being displayed on the monitor. This resolution is not only a part of the image information but also the operating parameter of the monitor. Therefore, the resolution is a kind of information leaked by equipment, and also belongs to the information of equipment.

When electronic equipment is working, the two types of EM information leakage would occur simultaneously with an EM radiation. That means, the same signals of EM leakage contain multi-dimensional information with different connotations. Information from different dimensions is mostly independent. We can identify the required information from the same EM signal according to specific purpose. In order to identify information in different dimensions, we usually adopt different identification methods accordingly.

B. MODEL OF MULTI-DIMENSIONAL INFORMATION

We propose a model of multi-dimensional information for EM leakage, as shown in Fig.3. Unintentional EM leakage occurs when electronic equipment is in operation. Detecting the leaked EM signals can obtain the hidden information. There are different information can be got from the same signals by respective identification methods, which constitute the multi-dimensional information of EM Leakage. Any one dimension of information can be a kind of information leaked by the equipment, or information of the equipment itself, or both.

The multi-dimensional Information can be represented by formula (1):

$$I = \sum_{k=1}^{N} I_k \tag{1}$$

where I is the N-dimensional Information from EM leakage, including leakage information by equipment and information of equipment; I_k is the information in k-th dimension, which

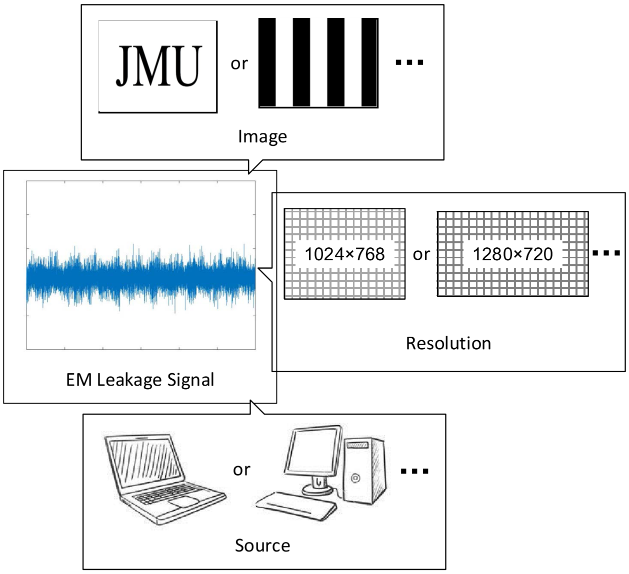


FIGURE 4. Multi-dimensional Information of EM Leakage from monitor.

can be expanded by formula (2):

$$I_k = D_k(S) \tag{2}$$

where S is the EM signal leaked form equipment; D_k is the targeted method for identifying the information in the k-th dimension.

C. MULTI-DIMENSIONAL INFORMATION LEAKED FROM MONITOR

We take the EM information leakage of computer monitors as an example to further illustrate the multi-dimensional information model. When the monitor displays images, it could leak EM radiation unintentionally. As shown in Fig. 4, there are at least three kinds of information hidden in the EM signals leaked by the monitor: image being shown, resolution of image/monitor, and EM characteristics of the monitor.

The image being shown on the monitor can be reconstructed from the EM leakage signals under certain conditions. According to the model introduced in Section 2.B, the image being shown is a kind of information leaked by equipment. The image is not inherent information of the monitor itself. The image information is leaked accompanying with the EM radiation from the monitor when it is being processed by the monitor.

Most computer monitors can work with different resolutions. When image is shown on monitor, the resolution of the image would be adjusted automatically to match the resolution of the monitor. The resolution is not only the structural information of the image, but also represents the operating parameters of the monitor at that moment. As we have mentioned before, the resolution belongs to both the information leaked by equipment and the information of equipment.

Every type of monitor has unique electrical characteristics, so the EM radiation of monitor would have some EM characteristics which can be called EM fingerprint. EM fingerprint

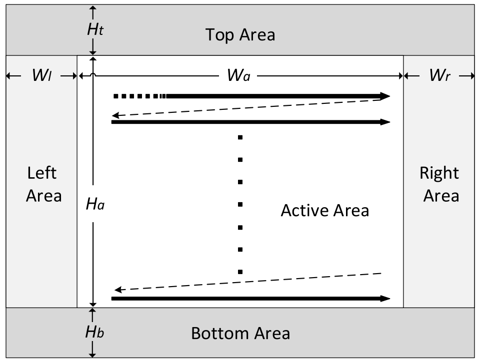
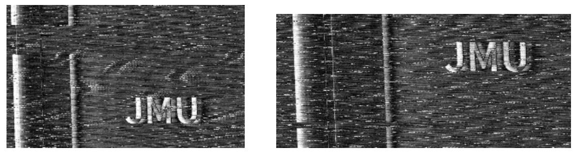


FIGURE 5. Principle of monitor showing image.



(a) (b)

FIGURE 6. Reconstructed images: (a) image resolution of 1024 × 768 (b) image resolution of 1280 × 720.

exists in all the EM radiation of monitor and is the inherent information of monitor. Therefore, it is the information of equipment based on our model.

The above three kinds of information constitute the three dimensions of the multi-dimensional information of EM leakage form monitor. In traditional way, in order to identify them from EM leakage signals, it is necessary to analyze their generation principles and characteristics.

1) IMAGE INFORMATION LEAKED BY MONITOR

Computer monitors display images by progressive scanning [20], as shown in Fig.5. Image data is transmitted to the monitor in the form of a sequence, line by line from top to bottom, pixel by pixel from left to right, and displayed on the monitor. The sequence of the image data consists of two parts: effective image signal and synchronization signal. The effective image signal constitute the visible image, which is displayed in the active area shown in Fig.5. The synchronization signal will not be shown on the monitor. EM radiation will be leaked when the monitor is displaying the image, and the radiation signals will reflect the change of pixels in the image. Therefore, there exists image information leaked by the monitor in the EM signals. Since the EM signal leakage and the showing image are synchronous, the image can be recovered from the leaked EM signal sequence according to the principle of monitor showing image. Fig.6 shows the examples of image reconstructed from the leaked EM signals. So, the method for identifying image information leakage is to extract the image features from the radiated EM signals.

2) RESOLUTION INFORMATION

The computer monitor can work in different resolution modes. The resolution information can be extracted from

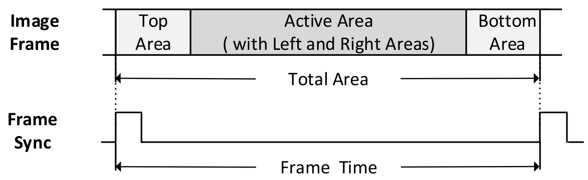


FIGURE 7. Frame synchronization.

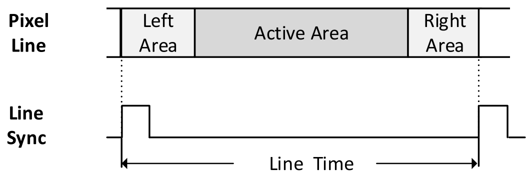


FIGURE 8. Line synchronization.

TABLE 1. Resolution and synchronization.

Resolution/ Active Area (Pixel)	Total Area (Pixel)	Refresh Rate/ Frame Frequency (Hz)	Frame Time (ms)	Line Frequency (kHz)	Line Time (us)
1024×768	1344×806	60	16.7	48.363	20.7
1280×720	1650×750	60	16.7	45	22.2

the synchronization signals in the image data sequence. The synchronization signals are invisible, hidden in the top, bottom, left, and right areas shown in Fig.5. The synchronization signals in these four areas are not shown on the monitor, but they also can leak EM radiation just like the effective image signals in the active area. The four areas and the active area constitute the total area of the monitor, and they can be calculated by the following two formulas:

$$ActiveArea = W_a \times H_a \tag{3}$$

$$TotalArea = (W_a + W_l + W_r) \times (H_a + H_t + H_b) \tag{4}$$

The synchronization signal includes frame synchronization and line synchronization. The frame synchronization signals in the top and bottom areas are used to segment the image signals sequence to frames of image, as shown in Fig.7. The line synchronization signals located at the left and right areas can separate a frame of image into pixel lines for progressive scanning, as shown in Fig.8.

It can be seen that the synchronization signal is periodic. So the identification method for the synchronization signal is mainly to find the periodic characteristics from the EM leakage signal. With the synchronization signal detected, the resolution information can be obtained according to the standard According to VESA and industry Standards and Guidelines for Computer Display Monitor Timing [20]. Table 1 illustrates the relationship between the resolution and the synchronization signal with two examples. The resolution represents how the pixels are arranged in the active area. The frequency of the frame synchronization is known as the refresh rate of the monitor.

The resolution information is leaked by the monitor along with the image information. It is not only the operating

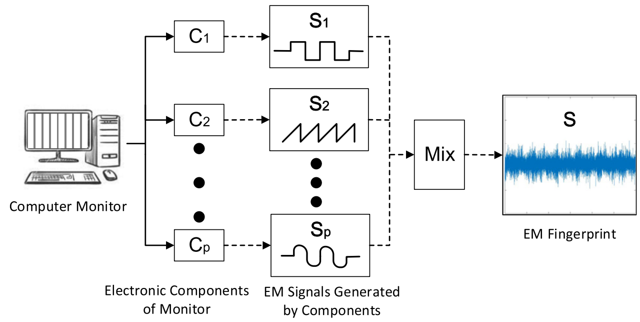


FIGURE 9. EM fingerprint.

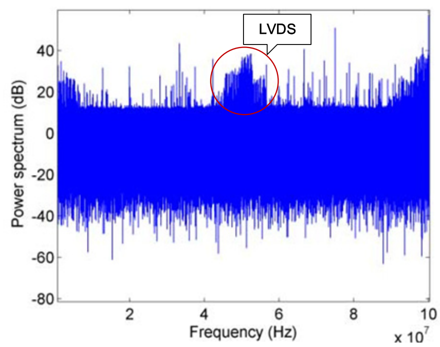


FIGURE 10. Example of EM fingerprint.

parameter information of the monitor itself, but also an additional part of leaked image information that can be used to reconstruct the image.

3) EM FINGERPRINT OF MONITOR

Electronic digital circuitry of monitor generates many periodic signals such as clocks and oscillators [21]. As shown in Fig.9, a computer monitor is assembled with various electronic components. Each of these components generates its own EM leakage. Since most of the components are digital circuits, the clocks and oscillators in the circuit will generate periodic signals, which endow the EM leakage signals with periodic characteristics. These periodic characteristics are correlate with the performance parameters of the electronic components such as running speed and processing capacity. EM signals of each component are mixed together in various ways, such as accumulation and modulation, to form a composite EM leakage signal with the unique characteristics of the monitor. The composite EM leakage signal is identifiable, which can be regarded as EM fingerprint. It is worth mentioning that the generation and mixing of EM leakage signals both are unintentional, which are shown in Fig.9 with dotted lines. So EM fingerprint is the inherent characteristic of electronic equipment.

It is possible to identify the type of electronic equipment that is responsible for the EM leakage by analyzing the EM fingerprints. This process is also known as EM leakage source identification.

For example, Fig.10 is the spectrum of the DELL E152FPC computer monitor [22]. The amplitude peak of the signal component near 57 MHz, marked by the red circle in Fig.10, exactly comes from the low-voltage differential signaling (LVDS) component of the monitor. The signal near 57Hz matches the clock signal which transmitted through LVDS. Therefore, this signal component can be used as part of the EM fingerprint of the monitor.

III. CNN FOR IDENTIFYING MULTI-DIMENSIONAL INFORMATION LEAKAGE

In this section, a method for multi-dimensional information identification will be introduced. The method is verified by identifying the EM information leakage of computer monitors. With this method, the content of image displayed, resolution and type of the monitor can be identified from the same EM radiation signals leaked unintentionally from the monitor. We think this method can also be adjusted to other electronic devices, which will be our future work.

A. RELATED WORK

Before we proposed the concept of multi-dimensional EM information, each dimension of the EM information leakage was considered separately by researchers. In general, traditional EM leakage identification methods need to know which features are related to information leakage in advance. The identification process is to look for these defined information leakage features in EM signals.

1) EM LEAKED IMAGE RECOGNITION

Since the first reported experiment of eavesdropping the image information from video display units, image reconstruction becomes a necessary means of EM leaked image recognition. There are some methods without reconstructing the image for determining whether or not image information leaks. Some of these methods determine the image leakage by looking for the synchronization signals of image [23], [24]. A method is to determine whether there is multi-line text image information leakage by seeking the line spacing feature of text [25], which is only valid for the multi-line text and not for single-line text and non-text images. However, the content of leaked image cannot be recognized by these methods without image reconstruction. These methods are mainly to search the specific characteristics that can prove the leakage of image information rather than to obtain the information of image. Therefore, image reconstruction is the most feasible method to recognize image from EM leakage so far. While image reconstruction requires some strict conditions, the most important of which is synchronization signal. According to the analysis in Section II.C, rearranging the 1D EM leakage signals to recover the 2D images needs the guidance of frame synchronization and line synchronization signals. Due to the disturbance of detection instruments and EM environment, it is usually necessary to adjust parameters manually in the image reconstruction process even if the synchronization signal is obtained.

2) RESOLUTION RECOGNITION

As we introduced in section II.C.2, the resolution matches the synchronization signals. If the EM leakage signal contains resolution information, some periodic characteristics can be found in the signal. These periodic characteristics are due to the periodic EM radiation produced by the synchronization signals, so that the periods are consistent with the intervals of the synchronization signals. Therefore, the available resolution recognition methods are to find the periodic signals on the spectrum of the EM leakage signal and match the resolution parameters [23], [24].

3) EM LEAKAGE SOURCE IDENTIFICATION

Some experiments have proved that although the LCD products and the input signals followed the same interface standard, the EM leakage of the different LCDs differed substantially [18]. The available methods of EM leakage source identification are almost based on signal analysis and processing such as dimensionally aligned signal projection [21], cyclic spectrum [22], frequency-modulated and amplitude-modulated [26], etc.

B. METHOD OF MULTI-DIMENSIONAL EM INFORMATION RECOGNITION BASED ON CNN

For traditional EM leakage identification, the definition and extraction of leakage features is different in each dimension, and the identification methods are also various. If we follow the traditional way, as the number of dimensions of EM leakage information increases, more and more identification methods will be required. So the recognition work will be too complicated. Therefore, we try to find a unified method to identify the EM leakage information in all dimensions.

In recent years, Deep Learning [27] has been widely used in recognition of various targets. As a typical Deep Learning algorithm, CNN [19] can automatically extract the features of data with its convolution processing. CNN has been proved to have a good performance in the field of image recognition [28]–[31] and signal recognition [32]–[34]. Therefore, we take the advantages of CNN in image and signal analysis to identify the information leakage in EM radiation.

We present a CNN based method for identifying multi-dimensional EM information leakage from the computer monitor. Fig.11 is the diagram of our recognition method. We trained three CNN classifiers for the three dimensional information of image, resolution and EM fingerprint contained in the EM leakage of computer monitor. Three classification results were combined to obtain three dimensional information of EM leakage from the monitor. The three classifiers are derived from the same CNN architecture we designed. Ideally, if we want to accommodate changes in the dimension of EM information, it is just to add or remove classifiers accordingly. The advantage of this method is that it is no need to define the information feature for each dimension. During the identification process, the CNN can extract the features of information leakage automatically.

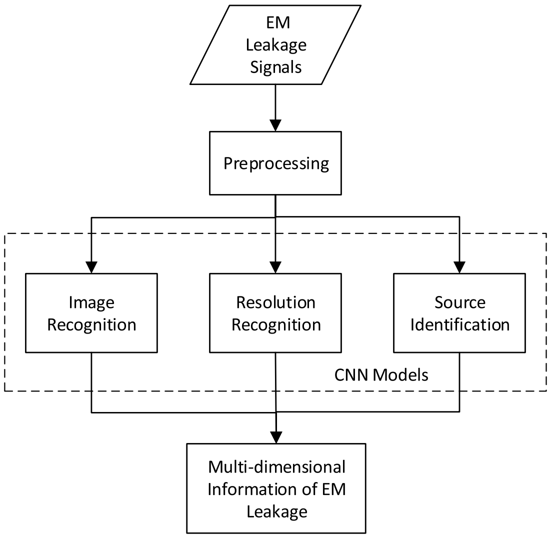


FIGURE 11. Multi-dimensional EM information leakage identification.

1) PREPROCESSING

Before the classification, the EM leakage signal is preprocessed uniformly. The EM signal has been collected in the time domain. According to the analysis in section II.C, all the information of the three dimensions have some periodic features. These periodic features are the critical basis of identification. Although our method does not need to specify these periodic features in advance, for facilitating the automatic extraction them, we transform the collected time domain signal into frequency spectrum. The means of transformation is fast Fourier transform (FFT):

$$\mathrm{X}(k) = \sum_{n=0}^{N-1} x(n)e^{-j2\pi kn/N} \quad \mathrm{k} = 0, 1, \cdots, N-1. \tag{5}$$

where $\mathrm{X}(k)$ is transformed spectrum sequence in frequency domain, $x(n)$ is the original signal sequence in time domain, N is the length of sequence. Fig.12 shows the EM leakage signal before and after preprocessing. The signal came from the EM leakage in Fig.6 (b), which is generated by a monitor displaying the "JMU" image with the resolution of 1280 × 720. The preprocessed spectrum can better represent the signal features in frequency domain, which is conducive to improving the classification performance of CNN.

2) PROPOSED CNN ARCHITECTURE

The EM leakage signal we captured is 1D. The image information leakage can be regarded as a 2D image hidden in the 1D time domain signal. The resolution and EM fingerprint of the monitor are also in the form of 1D signal. Therefore, we designed a Multi-dimension Identification Convolutional Neural Network (MD-CNN) to identify the multi-dimensional information leakage of the monitor with 1D convolution filter. The architecture of MD-CNN is indicated in Fig.13, which includes two 1D convolution layers, two max-pooling layers and a fully-connection layer. The parameter design of MD-CNN architecture is listed in Table 2.

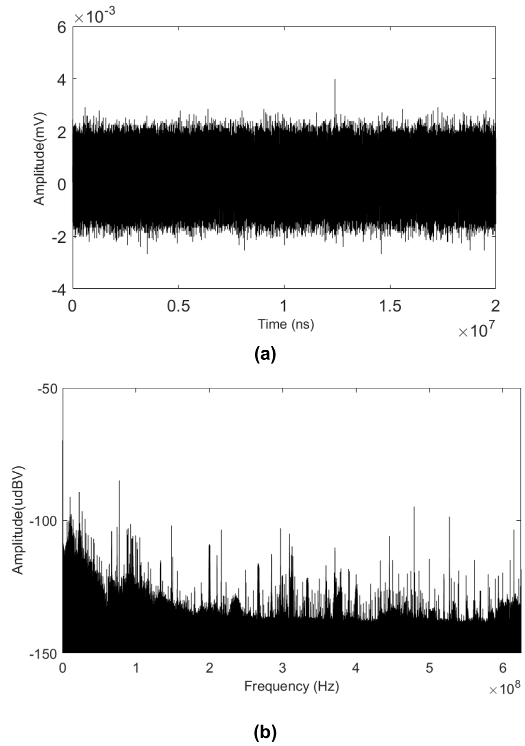


FIGURE 12. EM Information leakage signals (a) in time domain (b) in frequency domain.

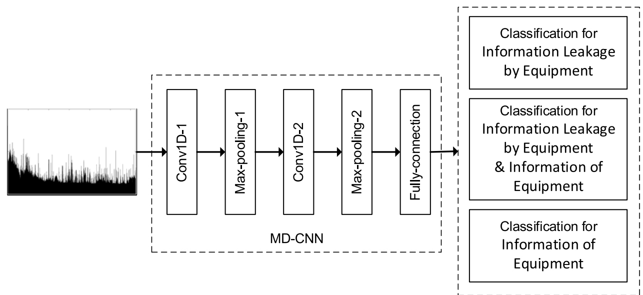


FIGURE 13. MD-CNN for multi-dimensional information identification.

TABLE 2. MD-CNN architecture.

Layer	Input size	Input channel	Filter Size	Stride	Output channel	Output size
Conv1	16384	1	160	4	16	4096
Pooling1	4096	16	2	2	16	2048
Conv2	2048	16	40	2	16	1024
Pooling2	1024	16	2	2	16	512
Fully-connection	512	16	-	-	-	Class

The function of the convolution layer is to extract the features of EM leakage samples. The 1D convolution operation slides the window of convolution filter to extract the local features of the input spectrum orderly:

$$X^{(L+1)} = X^{(L)} \otimes W^{(L)} + B^{(L)} \tag{6}$$

where L index the layers of the network, $X^{(L)}$ and $X^{(L+1)}$ are the input and output feature matrix in the Lth layer, respectively. Then, $W^{(L)}$ is the weight vector, $B^{(L)}$ is the bias vector.

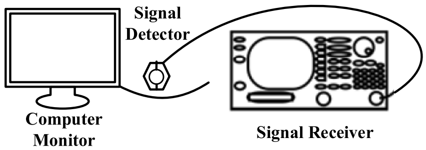


FIGURE 14. Signal collection setup.

We use the Rectified Linear Units (ReLU) [29], [35] as activation function, as shown in (7). It helps to restrain the overfitting of deep learning. Compare with previous sigmoid and tanh function, ReLU activation function could alleviate the vanishing gradient problem and improve the learning speed of the neural networks.

$$f(x) = max(0, x) \tag{7}$$

Combining the conv1D and the ReLU, the operation can be expressed as the following formula:

$$X^{(L+1)} = f(X^{(L)} \otimes W^{(L)} + B^{(L)}) \tag{8}$$

Furthermore, we take the dropout [36] operation after the convolution to prevent the neural network from overfitting, as shown in (9) and (10).

$$r_{i,j}^{(L)} \sim Bernoulli(p) \tag{9}$$

$$x*_{i,j}^{(L)} = x_{i,j}^{(L)} \times r_{i,j}^{(L)}/p \tag{10}$$

where $x_{i,j}^{(L)}$ is an element of the $X^{(L)}$ that is indexed by i,j. For the dropout, $r_{i,j}^{(L)}$ is an independent Bernoulli random variable with probability p of being 1, and it has the same shape as $x_{i,j}^{(L)}$. With the probability p, $x_{i,j}^{(L)}$ is kept and scaled up by $1/p$ to output $x^*_{i,j^{(L)}}$ independently, otherwise it is dropped which means $x^*_{i,j^{(L)}}$ outputs 0. In our work, p is set as 0.5.

Moreover, the Adam optimizer is applied to update the weight parameter of the network with the loss function of cross entropy.

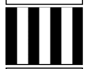
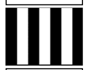
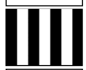
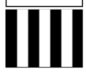
IV. EXPERIMENT FOR IDENTIFYING MULTI-DIMENSIONAL INFORMATION LEAKAGE

A. DATASET

We collected eight types of EM leakage samples with a signal receiver (NI PXIe-5162) and a signal detector (A.H.Systems BCP-620) from two types of computer monitors, as shown in Fig.14.

Each sample contains three-dimensional information: image, resolution and leakage source. There are two classes of information on each dimension, as shown in Table 3. In other words, each sample has three classification labels belonging to three dimensions. There are 1,000 samples of each type, 8,000 samples in total, which compose the data set. The samples were collected with three different sampling rates of 2MS/s, 208MS/s, and 1.25GS/s. It should be noted that the signal-to-noise ratio (SNR) of EM leakage signals is originally quite low. For this reason, the typical EM information leakage detection environment is EM shielding chamber, where the interference from environmental noise is minimal.

TABLE 3. Composition of dataset.

Type	Information Dimensions			Samples
	Image	Resolution	Source	
1	JMU	1024×768	DELL OptiPLex3240	1000
2		1024×768	PHILIPS HWE9220F	1000
3	JMU	1024×768	PHILIPS HWE9220F	1000
4		1024×768	DELL OptiPLex3240	1000
5	JMU	1280×720	DELL OptiPLex3240	1000
6		1280×720	PHILIPS HWE9220F	1000
7	JMU	1280×720	PHILIPS HWE9220F	1000
8		1280×720	DELL OptiPLex3240	1000

We have collected samples in various complex environments without shielding measures, which further reduced the SNR and increased the difficulty of identification actually.

The experiment is designed to verify our new way of EM information leakage identification: one method can identify multiple information in a single signal simultaneously. Although we only selected three dimensions of information from computer monitors in this paper, we have reason to believe that our idea can be applied to more electronic devices and more information dimensions.

B. RESULTS

We used the MD-CNN method proposed in Section 3.B to conduct experiments in three dimensions. There are three binary classification experiments with the same algorithm: image recognition, resolution recognition and leakage source identification. The three dimensional information can be obtained from the same EM signal simultaneously by three parallel CNN classifiers. The experimental data and classification labels are shown in Table 3. We implemented the five cross-validation for each experiment. All the experiments have been validated for five times by taking turns to select different one fifth of samples as the testing set, and the rest 6,400 samples as the training set. The hyper parameters during the training process are set as follows: the batch size is set to 100, the learning rate is initialized to 0.001, and the epoch is 30.

We compared the performance of our MD-CNN algorithm in each information dimension with popular deep learning algorithms: AlexNet [37], GoogleNET [38] and VGGNet [39], as shown in Table 4. The convolution kernels of these three algorithms are in 2D structure, but the sample is the 1D signal. Therefore, we segmented the original sample into a 2D spectrum to fit the 2D convolution. The accuracy

TABLE 4. Performance comparison among different algorithms.

Algorithm	Image		Resolution		Source	
	Accuracy (%)	F1 (%)	Accuracy (%)	F1 (%)	Accuracy (%)	F1 (%)
MD-CNN	**78.99 ± 0.78**	**76.22 ±3.51**	**79.39 ± 0.81**	**80.82 ± 2.20**	**90.31 ± 0.34**	**90.84 ± 0.50**
AlexNet	72.26 ±1.41	67.52 ±4.95	73.48 ±0.85	71.14 ±0.49	76.67 ± 0.97	77.66 ± 0.85
GoogleNet	68.35 ±1.04	73.27 ± 0.88	69.51 ± 1.11	71.70 ±6.34	77.06 ± 0.34	77.25 ±2.36
VGGNet	50	-	50	-	50	-

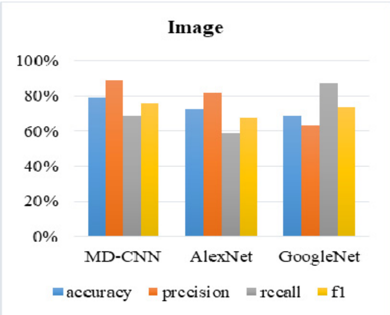


FIGURE 15. Performance on image recognition.

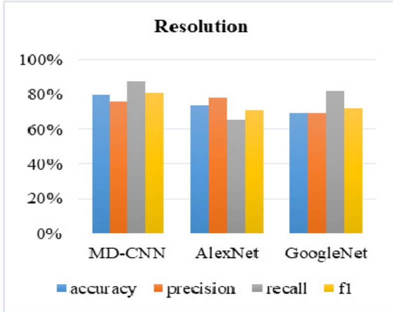


FIGURE 16. Performance on resolution recognition.

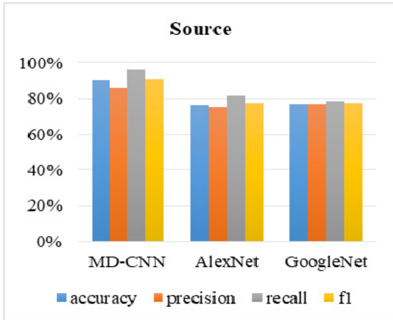


FIGURE 17. Performance on leakage source identification.

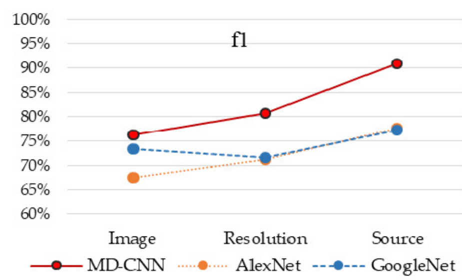


FIGURE 18. Performance on different dimensions of EM information.

and f1 were used as the key evaluation metrics. The comparison of experimental results is recorded in Table 4, it shows that our algorithm is superior to other algorithms in all three dimensions. The experimental results indicate that VGGNet has the worst performance in all dimensions. VGGNet could not distinguish the test samples at all, it predicted all the samples to be one category actually, so the values of the f1 are not recorded in Table 4.

In order to compare the performance of algorithms more intuitively, we drew performance evaluation charts for each dimension, as shown in Fig.15-17. Each figure compares the four algorithms by four performance indicators: accuracy, precision, recall, f1. The VGGNet was excluded from the following performance comparisons because of its poor performance. The details will be discussed in Section V.B.

It is found that the same algorithm turn out diverse performance on each dimension. as shown in Fig.18. We will analyze the reasons behind it in Section V.C.

V. DISCUSSION

A. COMPARE WITH AVAILABLE IDENTIFICATION METHODS

The available EM leakage identification methods usually only concentrate on a certain dimension of information in the leaked EM signal. They may have ignored the existence of multiple dimensions of information in the same EM signal. The proposed multi-dimensional information model is a novel theoretical description of EM information leakage.

In previous works, for identifying specific EM information leakage, it is necessary to define the specific leakage characteristics. In general, the identification methods are searching for the defined characteristics. For instance, the available image leakage recognition method is to reconstruct a recognizable image, the available resolution identification methods are to find the specific periodic signals, as introduced in Section III.A. The image characteristics is the specific characteristics should be defined and extracted artificially for the image leakage recognition. The periodic signals are the specific features that need to be known before identifying the resolution. By traditional way, each type of EM information leakage identification needs different leakage characteristics to be artificially defined. However, there are some hidden characteristics that are not easy to define and extract. For example, identifying the EM fingerprint of the leakage source, as illustrated in Section III.A.3). Only by disassembling the monitor and measuring the EM characteristics of electronic components one by one, it can be determined that the peak characteristics shown in Fig.10 are from LVDS.

Our method uses a fixed CNN to automatically extract hidden features of multiple dimensions of information in EM signals, avoiding the trouble of artificial definition and extraction. It provides a new way for EM information leakage identification. Experimental results show that our method can extract EM leakage information from different dimensions.

Moreover, due to the low sampling rate, such as 2MS/s, the image cannot be reconstructed from some experimental samples at all. It means that the traditional method is unable to identify the image content in the case of insufficient sampling rate. By contrast, our method can recognize image information with such a low sampling rate. Therefore, our method can reduce the precision requirement of EM detection instrument, so as to reduce the hardware cost of identification.

In future work, we will try to verify the effectiveness of our algorithm on more information dimensions and more electronic equipment, then optimize the algorithm to improve identification performance.

B. COMPARE WITH OTHER DEEP LEARNING METHODS

Some Machine Learning algorithms require the definition of specific features or attributes. However, it is difficult to define the information features of EM signals. In fact, we have also tried other Deep Learning methods, such as Long Short Term Memory (LSTM) [40]–[42]. Since the length of each EM leakage sample is more than 16,000, it is a burden for the implementation of LSTM algorithm, so our current computing power cannot carry out the LSTM experiments smoothly. For the future research, if we can find a suitable data embedding method, LSTM should also be able to be applied to EM information leakage identification.

In the end, we chose the Deep Learning method CNN to extract the information leakage features in the EM signal. At present, the popular CNN structures mostly adopt the 2D convolution kernel, and there is no CNN designed for EM leakage identification. After trying popular 2D CNNs, we decided to design a 1D CNN for EM signals. This is because that the original EM signal appears as a 1D sequence. If the 1D signal sample is artificially converted into 2D input, the original information is broken to some extent. This results in reduced identification performance.

The experiment results in Section IV.B show that the performance of our MD-CNN is better than AlexNet and other two popular Deep Learning algorithms in every dimension. This proves that the 1D convolution of MD-CNN can better adapt to the 1D signal samples.

The experiments indicate that VGGNet is not suitable for EM leakage identification at all. The reason is that the convolution kernel size of VGGNet is too small to extract the features of EM signal sample in large size. In order to extract signal features in the frequency domain with a wider range, we designed the convolution kernel with a larger size than other CNNs. This also makes MD-CNN have better performance in EM information leakage identification.

C. PERFORMANCE ON DIFFERENT DIMENSIONS

Fig.18 shows that MD-CNN has different performance of information leakage identification in the three dimensions. This performance difference also occurred with AlexNet and GoogleNet. After analyzing the EM signal samples, we consider that this is caused by the sample differences on diverse dimensions.

Since the samples came from the EM radiation generated by the electronic equipment, the value of the sample sequence is actually the amplitude of the EM radiation. The differences between samples are reflected in the intensity and variation of the amplitude. From the sample data, the difference of EM radiation amplitude between the two types of monitors is relatively obvious. The monitor is also known as the leakage source. In contrast, the difference of EM radiation caused by the change of image content and resolution is relatively small. Therefore, the performance of leakage source identification is better than image and resolution recognition.

D. MULTI-LABEL CLASSIFICATION

In our opinion, the identification for multi-dimensional information leakage can similarly be regarded as a multi-label classification [43], [44] for the leaked EM signals. So our method can be considered as a problem transformation method [45], and a label powerset [46] method especially. It is to transform the multi-label classification problem into an ensemble of multi-class classification problems. The identification for multi-dimensional EM leakage information can be thought of an independent multi-classification problem. The labels which belong to different dimensions are unrelated.

VI. CONCLUSION

In the traditional way, one-to-one strategy is adopted to use the targeted identification method for each type of EM information leakage. We proposed an innovative one-to-many strategy to solve various EM information leakage problems.

In this paper, we took computer monitor as an example to analyze multiple information leakage caused by the same unintentional EM radiation from electronic equipment.

An innovative model of multi-dimensional EM information was presented. This model can explain EM information leakage more comprehensively and provide new theoretical basis of the research of EM information leakage identification.

We proposed MD-CNN as a novel method of identifying multi-dimensional information leaked from unintentional EM radiation. The MD-CNN has the large-size 1D convolution kernels and the suitable network structure specially designed for EM leakage signals, which makes it superior to the other CNNs in EM information leakage recognition. Different from traditional identification methods, this method can identify multiple leakage information from the same EM radiation signal. The multiple dimensional information can be obtained simultaneously by the MD-CNN. And it overcomes the defect that the previous methods need to define the specific identification feature artificially. It provided a new way for identifying EM information leakage by using CNN to automatically extract leakage features.

We collected real EM leakage signals from computer monitors and established experimental data set. Experiment result indicates the proposed method can recognize different images, resolution and source types simultaneously. Comparative experiments show that MD-CNN is effective and better than the several available CNN algorithms.

Our work is a new attempt on the research of EM information leakage. The concept, the algorithm design, the data collection and the experiments are all from scratch. As a future work, we plan to continue collecting EM leakage signals from more electronic devices and in more dimensions to extend our data set. On the basis of enhancing the data set, we plan to practice our information leakage identification algorithm for more objects, and keep improving the algorithm.

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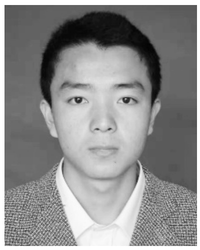

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