Invisible Backdoor Attacks Using Data Poisoning in the Frequency Domain

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ABSTRACT
With the rapid development and broad application of deep neural networks (DNNs), backdoor attacks have gradually attracted attention due to their great harmfulness. Backdoor attacks are insidious, and poisoned models perform well on benign samples and are only triggered when given specific inputs, which then cause the neural network to produce incorrect outputs. The state-of-the-art backdoor attack work is implemented by data poisoning, i.e., the attacker injects poisoned samples (some samples patched with a trigger) into the dataset, and the models trained with that dataset are infected with the backdoor. However, most of the triggers used in the current study are fixed patterns patched on a small fraction of an image and are often clearly mislabeled, which is easily detected by humans or some defense methods such as Neural Cleanse and SentiNet. Also, it is difficult to be learned by DNNs without mislabeling, as they may ignore small patterns.

In this paper, we propose a generalized backdoor attack method based on the frequency domain, which can implement backdoor implantation without mislabeling the poisoned samples and accessing the training process. It is invisible to human beings and able to evade the commonly used defense methods. We evaluate our approach in the no-label and clean-label cases on three benchmark datasets (CIFAR-10, STL-10, and GTSRB) with two popular scenarios, including self-supervised learning and supervised learning. The results show that our approach can achieve a high attack success rate (above 90%) on all the tasks without significant performance degradation on main tasks. Also, we evaluate the bypass performance of our approach for different kinds of defenses, including the detection of training data (i.e., Activation Clustering), the pre-processing of inputs (i.e., Filtering), the detection of inputs (i.e., SentiNet), and the detection of models (i.e., Neural Cleanse). The experimental results demonstrate that our approach shows excellent robustness to such defenses.

KEYWORDS
Neural Networks, Backdoor Attack, Data Poisoning, Frequency Domain

Figure 1: The examples of backdoor attacks. a) is the original image, b), c), and d) are images patched with the trigger proposed by Badnets [13], TojanNN [23] and our work. Particularly, Badnets and TrojanNN samples are always labeled to the target label (e.g., car), but ours is with a clean label.

1 INTRODUCTION
With the significant improvement of computing power, deep learning has been developed rapidly, in particular, supervised learning trained on labeled datasets and self-supervised learning trained on pretext tasks with unlabeled datasets, which have been widely applied in various areas and have profoundly changed people’s production and lifestyle, such as face recognition [29, 38, 50], speech recognition [2, 43], autonomous vehicles [1, 25], and remote diagnosis [32].

The ubiquitous and successful application of deep learning in various fields simultaneously brings new security issues, such as adversarial attacks [42, 51, 57] and backdoor attacks [8, 13, 23]. Unlike adversarial attacks that explore the intrinsic vulnerability of DNNs in the inference phase, backdoor attacks always poison models in the training phase, which could perform well on benign samples but output false output when fed backdoor samples. For example, suppose a company’s face recognition access control system suffers a backdoor attack (e.g., a pair of glasses with a unique shape can trigger the backdoor). In that case, the system will recognize the adversary wearing the glasses as an employee within the company, posing a potentially serious security risk.

State-of-the-art data poisoning-based work faces the bottleneck of insufficient stealthiness or poor robustness, as shown in Figure 1. 1) the poisoned samples have fixed trigger patterns and wrong labels in labeled datasets and fixed trigger patterns in the unlabeled dataset, which can be effortlessly perceived by human beings. 2) the
fixed trigger can be detected and reconstructed by some defenses, such as Neural Cleanse [46], SentiNet [9].

Inspired by [26, 53, 54], i.e., DNN models can learn the signals in the frequency domain and a slight change in the frequency domain can influence all the pixels in the spatial domain that are invisible to humans, we believe that the frequency domain-based backdoor attack approach can solve the problems of the previous study mentioned above. However, there are some challenges in designing the frequency domain-based backdoor attack as below.

**Challenges in designing frequency domain backdoor.** C1: Be robust to defenses that preprocess the input, e.g., filters. C2: Bypass defenses based on trigger detection. The state-of-the-art backdoor defenses are based on detecting a specific trigger pattern in the spatial domain. C3: Simultaneously ensure the learnability and stealthiness of the frequency backdoor. Trigger with higher frequencies and intensities is more accessible for DNN models to learn but more able to be perceived by humans.

In this paper, we propose an adaptive trigger selection algorithm to deal with the challenges above, which contains three phases. In the first phase, we select multiple frequencies robust to some commonly used filters (e.g., Gaussian Filter) as candidates (address C1). In the second phase, we select frequencies that could make the trigger have different patterns on different images in the spatial domain to apply our modification in the frequency domain. Further, the more significant the difference between the trigger patterns among all the images, the more likely our attack will bypass such defenses. (address C2). In the third phase, we choose a target intensity whose value is slightly more significant than the average intensity among the original images but no greater than a threshold at each frequency selected, considering the frequency’s location and the value of the average intensity (address C3).

We evaluate our attack in two neural network learning scenarios, including self-supervised and supervised learning. For self-supervised learning, we pre-train ResNet-18 [17] on the poisoned CIFAR-10 [20] dataset (i.e., some images are patched with our frequency trigger) as the feature extractor using the popular methods SimCLR [6] and MOCO V2 [7], and then transfer to the downstream tasks, including CIFAR-10, STL-10 [10] and GTSRB [41]. We train ResNet-18 on the poisoned CIFAR-10 and STL-10 datasets for supervised learning. The experimental result demonstrates that our attack achieves over 90% success rate on the poisoned samples of all the datasets, and only about 2% performance degradation on the main tasks is incurred. Furthermore, we use PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity) to evaluate the changes to the original images due to our frequency trigger. The average PSNR on CIFAR-10 and STL-10 datasets is 24.11 and 26.94, respectively, and the average SSIM is 0.9024 and 0.9044, proving that our trigger has good stealthiness. In addition, We evaluate the bypass effectiveness of our attack against common backdoor detection methods, and the experimental result shows that our approach can bypass them all with high robustness.

**Contributions.** Our main contributions are outlined below:
- We propose a new invisible backdoor attack by designing a frequency trigger based on the statistical characteristics in the frequency domain. To the best of our knowledge, we are the first to achieve backdoor implantation on both no-label (i.e., self-supervised learning) and clean-label (i.e., supervised learning) scenarios without mislabeling the poisoned samples and accessing the training process.
- We design an adaptive algorithm to choose appropriate properties for our frequency trigger, proving to make the trigger stealthier and more robust to the current commonly used defense methods.
- We successfully implement an invisible backdoor attack in the frequency domain with over 90% attack success rate while guaranteeing the performance of the main task.

## 2 BACKGROUND AND RELATED WORK

### 2.1 Spatial Domain and Frequency Domain

The spatial domain, also called image space, is a domain in which the pixels of the original image can be manipulated directly. RGB and YUV are two common color spaces used to record or display color images in the spatial domain. Both of them are based on the perceptual capabilities of the human eyes. RGB describes the combination of red, green, and blue, while YUV represents luminance (denoted as “Y” channel) and chrominance (denoted as “U” and “V” channels) that describes the light intensity and carries color information. Since the YUV color space is closer to human vision than RGB and has better perceptual quality [30], YUV is increasingly used in the field of image processing [52].

The frequency domain provides a new perspective for image processing. In the frequency domain, the low-frequency components correspond to smooth regions in the image, and the high-frequency components correspond to edges in the image. The spatial domain and frequency domain can be transformed into each other by Fourier transform. DFT (Discrete Fourier Transform) and DCT (Discrete Cosine Transform) are the most classical transform methods. DCT is developed from DFT and is widely used in digital image processing because it has better energy aggregation in the frequency domain than DFT. The two-dimensional DCT and Inverse Discrete Cosine Transform (IDCT) are shown below.

\[ F(u, v) = \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} f(i, j) G(i, j, u, v) \quad (1) \]

where,

\[ G(i, j, u, v) = c(u) c(v) \cos \left( \frac{(i + 0.5) \pi}{M} u \right) \cos \left( \frac{(j + 0.5) \pi}{N} v \right) \quad (3) \]

and

\[ c(u) = \begin{cases} \sqrt{\frac{1}{M}}, & u = 0 \\ \sqrt{\frac{2}{M}}, & u \neq 0 \end{cases} \quad c(v) = \begin{cases} \sqrt{\frac{1}{N}}, & v = 0 \\ \sqrt{\frac{2}{N}}, & v \neq 0 \end{cases} \quad (4) \]

where DCT transforms an image of size \( M \times N \) from the spatial domain to the frequency domain of the same size (equation 1), and IDCT does the opposite (equation 2). \( F(u, v) \) represents the intensity at \((u, v)\) in the frequency domain, and \( f(i, j) \) represents the pixel values at \((i, j)\) in the color space.
2.2 Backdoor Attacks

Backdoor attacks in supervised learning. In the last decade, deep supervised learning has achieved great success and has been involved in various complicated tasks, including computer vision tasks [33, 36, 38], natural language process [12, 27, 28], graph learning [19, 49], and so on. Unfortunately, with the popularity of DNNs, they are suffering from many attacks. Backdoor attacks are mainly achieved by data poisoning, i.e., attackers train the victim DNNs in a poisoned training dataset with poisoned samples stamped with a trigger pattern (e.g., a small patch in the right-bottom corner of an image) relabelled to the target class. To enhance the stealthiness of the backdoor attack, on the one hand, several works have proposed invisible backdoor trigger generation approaches. Chen et al. [8] propose a blended injection strategy to make the pattern of the trigger blend with the background image better. Barni et al. [3] choose a sinusoidal signal (i.e., fringe patterns in the spatial domain) as the backdoor trigger. Liu et al. [24] utilize the natural reflection phenomenon to act as trigger. On the other hand, some studies try to achieve a backdoor attack in the clean-label scenario, preventing detection due to mislabeling. Turner et al. [45] first implement and discuss successful backdoor attacks under the clean label by utilizing adversarial examples and GAN-generated data. Barni et al. [3] add a global ramp signal on the uniform dark background of MNIST dataset [21] to make it detectable by the DNNs. Both results demonstrate that triggers that can cause global perturbations to the original images will be needed to achieve clean-label backdoor attacks.

Backdoor attacks in self-supervised learning. Unlike supervised learning, self-supervised learning trains the encoder on the pretext of tasks that leverage input data as supervision to help the encoder learn some critical features of the dataset. CLIP [31] is trained on a wide variety of images with a wide variety of natural language supervision, which are abundantly available on the internet. SimCLR [6] is proposed to learn the visual representations by contrastive learning, which learns representations by maximizing the similarity between differently augmented representations of the same example via a contrastive loss in the latent space. Inspired by SimCLR, MoCo v2 [7] improves the Momentum Contrast self-supervised learning algorithm by introducing blur augmentation and outperforming the SimCLR with smaller batch sizes and fewer epochs. At the same time, backdoor attacks against self-supervised learning have begun to gain widespread attention. Carlini et al. [4] propose a backdoor attack against CLIP by patching a trigger on the images and modifying the corresponding text descriptions. Jia et al. [18] propose a backdoor attack on the pre-trained encoder by designing an optimization function that aggregates the feature vectors of images with embedded triggers into the output space of the encoder. Saha et al. [37] utilize the training characteristics of contrastive learning to inject a backdoor to the model by patching a trigger on the images of the target class.

Backdoor attacks in frequency domain. Based on our observation, the frequency domain has natural stealthiness. Specifically, the slight changes in the frequency domain can cause invisible changes in the spatial domain, which are difficult to perceive by humans [40]. Previous studies have demonstrated that DNN models can perceive information in the frequency domain and that it tends to learn components from low-frequency to high-frequency [26, 53, 54]. Besides, Wang et al. [47] and Yin et al. [55] discuss the relation between the robustness, generalization of a DNN model and the frequency properties of training data in the frequency domain. Gueguen et al. [14] and Xu et al. [52] directly extract features from the frequency domain to classify images. Zeng et al. [56] analyze the frequency-domain characteristics of the current trigger, and they find that images patched with different triggers contain vital high-frequency components compared to the spectrum of clean images.

With the development of neural network interpretability in the frequency domain, several recent works have begun to study backdoor attacks from a frequency domain perspective. Wang et al. [48] try to inject the backdoor directly through the frequency domain. However, the proposed frequency trigger has a fixed pattern in the spatial domain, which can be easily detected. Hammoud et al. [16] proposed to find the frequencies which are sensitive to the decision of the DNN models as the position to inject frequency trigger; however, the method needs a clean model well trained on the dataset prepared to poison and needs to mislabel the poisoned samples when training the backdoored model.

In this paper, we propose an invisible backdoor attack taking advantage of the characteristics of the frequency domain, and we can inject a backdoor without mislabeling and access to the training process. The trigger overlaps the whole image which helps DNN models to learn the feature of the trigger, and this makes backdoor attacks successful in the scenario of clean-label supervised learning and no-label self-supervised learning because the model can perceive the features of original images and the trigger at the same time.

2.3 Backdoor Defenses

Due to the great harm caused by backdoor attacks, many defenses methods have been proposed in recent years, which are mainly divided into three types: the defenses against training data [5, 44], the defenses against model inputs [9, 11], and the defenses against models [15, 22, 46].

Defenses against training data. Activations of the last hidden layer reflect high-level features used by the neural network to predict results. Chen et al. [5] propose an activation clustering method, the activations of inputs belonging to the same label are separated and clustered by applying a k-means cluster with $k = 2$ after dimension reduction, and one of the clusters is poisoned samples. These poisoned samples are removed or relabeled with an accurate label. Tran et al. [44] explore spectral signature, a technique based on robust statistic analysis, to identify and remove poisoned data samples from a potentially compromised training dataset.

Defenses against model inputs. SentiNet [9] is proposed to detect a potential attack region of an image using Grad-CAM [39] developed for model interpretability and object detection. Then, the region can be checked manually to identify poisoned inputs, i.e., samples with a trigger patched. Februus [11] train a generative adversarial network (GAN) to repair images automatically after removing the suspicious areas masked by Grad-CAM.
Defenses against models. Wang et al. [46] firstly propose the Neural Cleanse to detect whether a DNN model has been backdoored or not prior to deployment by reversing the trigger. The performance of reversing triggers further improved in TABOR [15] by utilizing various regularizations when solving optimizations. ABS [22] examines whether a given DNN model is backdoored or not by analyzing inner neuron behaviors. In particular, a neuron that significantly contributes to a particular output label regardless of inputs is considered a compromised neuron. And then, ABS generates a trigger for the compromised neuron using the stimulation analysis and utilizes the performance of the trigger to confirm if the neuron is truly backdoored.

3 DATA POISONING WITH FREQUENCY DOMAIN

3.1 Threat Model

We consider an attacker aims to poison a dataset by patching an invisible trigger on the part of the samples so that there is no need to control the training process of the models, and any DNN model trained on the dataset containing backdoor samples, either by supervised learning and self-supervised learning, will be implanted with a backdoor. Specifically, attackers have three main goals: effectiveness, stealthiness, and robustness. Effectiveness means that the model will have similar behavior to the benign model when processing samples without our trigger attached. However, it will misclassify samples patched with the trigger as a specific label with a high success rate. Stealthiness requires that backdoor triggers are invisible to humans so that samples patched with triggers can pass the manual check. Robustness represents two cases, one is that the trigger remains valid under some common defenses, and the other is that the performance of the model is significantly degraded if a defender tries to clear the trigger using some defenses against the input or dataset.

3.2 Overview

Figure 2 overviews our data poisoning attack approach, including two main components: Frequency Trigger Generation and Backdoor Injection. We aim to poison a dataset so that the DNN models trained on the dataset will be injected into the backdoor. Given an original dataset, we analyze the frequency distribution characteristics of the images in a preset target class and select a set of intensity values of proper frequencies in the frequency domain as triggers based on statistical features. To achieve our attack goals (see Section 3.1), we design adaptive triggers in the frequency domain with the following metrics: invisible to human beings, patterns that overlap with large areas of the images in the spatial domain, no specific pattern in the spatial domain and still exist after common data preprocessing. In the second phase, we transform the images in the target class from the spatial domain to the frequency domain using Fourier transform and inject our frequency trigger to generate a poisoned dataset.

3.3 Trigger design

As shown in [26, 53, 54], frequency domain information can be perceived by the DNN models, and its changes can affect all the pixels of the original trigger. This means that frequency triggers overlap the whole image and may take effect in the no-label or clean-label backdoor attack scenarios [3, 24, 45]. In addition, it is difficult for humans to perceive the changes in images if the intensity changes of specific frequencies are within a threshold, which means that the frequency domain may be a good way to insert triggers and utilize poisoning to achieve a backdoor attack. In this paper, we propose an approach for generating an adaptive frequency trigger of the following form:

\[
F_T(u, v) = \begin{cases} 
0, & (u, v) \notin v_T \\
|F_T(u, v) - F_n(u, v)|, & (u, v) \in v_T 
\end{cases}
\]

where \(F_T(u, v)\) and \(F_n(u, v)\) represent the intensity of the trigger and the original image at \((u, v)\) frequency, respectively, \(v_T\) represents the frequency we choose to change the intensity, and \(F_T(u, v)\) represents the target intensity we prepare to set for each selected frequency, and their selection follows the two objectives as below:

\[
v_T = \min_{(u, v)} \left\{ \text{Diff}(F_{(u, v)}, F_{\text{filter}}(u, v)) \right\}
\]

\[
\cap \max_{(u, v)} \left\{ \text{Discrete}(F_{(u, v)}) \right\}
\]

\[
|F_T(u, v) - F_n(u, v)| < \varepsilon
\]

where \(F_{(u, v)}\) and \(F_{\text{filter}}(u, v)\) are the set of intensities at the frequency \((u, v)\) of all the images in \(D_o\) and the images after filtering, \(\text{Diff}\) is to calculate the average differences of the intensity at the frequency \((u, v)\) among all the images, and \(\text{Discrete}\) is to calculate the dispersion of the intensities at the frequency \((u, v)\) among all the images, \(\varepsilon\) is the threshold lower than which changes are not perceived by humans. Equation 6 selects the frequencies with strong robustness against filter and defense methods based on trigger pattern detection, and Equation 7 sets intensities with high stealthiness. Finally, we patch our triggers into the image as follows:

\[
F'_n(u, v) = \begin{cases} 
F_n(u, v), & (u, v) \notin v_T \\
F_T(u, v), & (u, v) \in v_T 
\end{cases}
\]

Algorithm 1 illustrate our adaptive trigger generation process. Given a dataset \(D_t\) with \(N\) images that have been transformed to the frequency domain, we first try to select appropriate frequencies as a candidate, which can be robust to filters (line 5). And then, we select frequencies that can make significant differences between trigger patterns on different images in the spatial domain from the candidate as they help to bypass the current backdoor defenses based on trigger pattern detection (line 6). Finally, we set proper intensities at each frequency selected to make our trigger invisible (lines 7-8). For each channel, we calculate the mean value of the intensities at each frequency in \(v_T\) among all the images as the basic intensities (line 7), and then set values slightly more significant than the basic intensities but no greater than a threshold \(\varepsilon\) (the threshold is obtained from manual adjustment and observation) as the target intensities \(F_T\) (line 8). Up to now, we have finished the choice of our adaptive frequency trigger.

Especially, when selecting the frequencies candidate (lines 10-21), we first pass each image to the filter (line 11). For each channel, we calculate the average relative distance between the intensities
at each frequency of original images and the images after filtering (lines 13-15) and sort the distances from smallest to largest to obtain the corresponding frequencies (line 16). Then, we select the top 50 frequencies ranked high on all three channels as the candidate \( V_{\text{candidate}} \) (line 19). After the candidate frequencies are selected, we use a similar method to select the target frequencies (lines 22-32) at which the Coefficient of Variation (CoV) of intensities are the largest (the more significant the value of \( \text{CoV} \), the greater the dispersion of the data). The triggers in the spatial domain are formalized as follows:

\[
F_T(i, j) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F_T(u, v) G(i, j, u, v)
= \sum_{(u,v) \in \nu} (I_T(u,v) - F_n(u,v)) G(i, j, u,v)
\]

Since \( I_T(u,v) \) is a fixed value, to maximize the variance of trigger patterns (i.e., \( F_T(i,j) \)) on different images, we should select frequency at which intensities (i.e., \( F_n(u,v) \)) vary considerably among all the images. We calculate the CoV for each frequency in the candidate set \( V_{\text{candidate}} \) across all images (lines 24-26) and sort the CoV from the largest to the most minor (line 27) to get the corresponding frequencies. Finally, we pick a specified number (i.e., \( \text{TopN} \)) of frequencies that rank high on all three channels as the position of our frequency trigger \( v_T \) (line 30).

### 3.4 Backdoor Injection

After the backdoor trigger is generated, we can then implant it into the target class images of the dataset to build the poisoned dataset. Firstly, we transform the images in the target class from the spatial domain to the frequency domain using the Discrete Cosine Transform (DCT) after converting them into the YUV color space (see Section 2.1). Secondly, we inject our trigger into the images presented in the frequency domain by adding the intensity values of the trigger to that of images at the corresponding frequencies. Finally, we transform images back to the spatial domain using the Inverse Discrete Cosine Transform (IDCT), and then we get a poisoned dataset.

### 4 EXPERIMENT

#### 4.1 Experiment Settings

**Dataset and model.** We utilize three popular datasets in our experiments, including CIFAR-10 [20], STL-10 [10] and GTSRB [41]. And we choose ResNet-18 [17], a classic DNN model to evaluate our backdoor attack.

- **CIFAR-10** is one of the most commonly used datasets in the task of object classification, which consists of 60,000 \( 32 \times 32 \times 3 \) color images in 10 classes, with 50,000 training images and 10,000 testing images.
- **STL-10** is an image recognition dataset for developing unsupervised feature learning, deep learning, and self-taught learning algorithms. The STL-10 contains 5,000 labeled training images and 1,000 labeled testing images in 10 classes, and 100,000 unlabeled images. Each image has a size of \( 96 \times 96 \times 3 \).
- **GTSRB** is widely used in the task of autonomous driving, which contains 43 classes of traffic signs, split into 39,209 training images and 12,630 test images. The size of each image is \( 32 \times 32 \times 3 \).

**Scenarios.** We benchmark our attack approach under both self-supervised learning and supervised learning scenarios. For self-supervised learning, we use two widely used methods, SimCLR [6] and MoCo v2 [7] to pre-train ResNet-18 as an image encoder on the poisoned CIFAR-10 dataset and then use the encoder for the downstream datasets CIFAR-10, STL-10 and GTSRB to train downstream classifiers. We train ResNet-18 on the poisoned CIFAR-10 and STL-10 datasets for supervised learning. Note that for self-supervised learning, we implement them based on the implementation shown in [35] for SimCLR and [7, 34] for MOCO V2, and use their default training parameters and data transformations. For supervised learning, we apply the commonly used parameters and data transformation in order not to disturb the normal training process.

**Metrics.** We use the following four metrics to evaluate our approach:

- **Clean Data Performance (CDP)** evaluates the proportion of clean samples predicted as their ground-truth classes by classification models.
- **Attack Success Rate (ASR)** is the fraction of the poisoned images (i.e., the images embedded with our trigger) that are predicted as the target label we specify by the backdoored DNN models.
- **Peak Signal-to-Noise Ratio (PSNR)** is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. It’s commonly used to quantify the quality of images after processing.
- **Structural Similarity (SSIM)** is used for measuring the similarity between two images. Compared to PSNR, SSIM is more in line with the perception of human beings because it incorporates crucial perceptual phenomena, including both luminance masking and contrast masking terms.
Algorithm 1 Adaptive trigger generation algorithm in the frequency domain

Input: $D_t$: the dataset with the target label in the frequency domain; $N$: the number of the images in $D_t$; $(C, W, H)$: the shape of each image; $v$: all the frequencies of images; $TopN$: the number of frequencies to select; $\epsilon$: the threshold of intensities;

Output: $v_T$: the list of the frequencies selected; $I_T$: the list of the corresponding target intensities

1: $v = \{(1, 1), (1, 2), ..., (W, H)\}$
2: $D_t = \{x^n, n \in [1, N]\}$
3: $x^n = \{\mathbf{f}_{ch}^n(u, v), (u, v) \in v, c \in [1, C]\}$
4: $v_T = \text{NULL}, I_T = \text{NULL}$
5: $v_{\text{candidate}} = \text{SelectFrequencyRobustToFilter}(D_t)$
6: $v_T = \text{SelectFrequencyDiscrete}(D_t, v_{\text{candidate}})$
7: $I_T = \text{GetMeanValue}(D_t, v_T, ch, c \in [1, C])$
8: $I_T = \text{SetValue}(v_T, I_T, \epsilon)$
9: return $v_T, I_T$

10: Function $\text{SelectFrequencyRobustToFilter}(D_t)$
11: \{ $\{x^n_{\text{filter}}\} = \text{Filter}(x^n), n \in [1, N]$ \}
12: for $ch$ in $[1, C]$ do
13: \{ for $(u, v) \in v$ do \}
14: \begin{align*}
    \text{diff}(u, v) &= \text{Diff}(x^n, \{x^n_{\text{filter}}\}), n \in [1, N] \\
    \text{end for}
\end{align*}
15: \begin{align*}
    v_{ch} &= \text{AscendingSort} (\text{diff}(u, v), (u, v)) \\
    \text{end for}
\end{align*}
16: \begin{align*}
    v_{\text{temp}} &= \{v_{ch}, ch \in [1, C]\} \\
    v_{\text{candidate}} &= \text{CommonTop}(v_{\text{temp}}, 50)
\end{align*}
17: return $v_{\text{candidate}}$
18: end Function

22: Function $\text{SelectFrequencyDiscrete}(D_t, v_{\text{candidate}})$
23: for $ch$ in $[1, C]$ do
24: \{ for $(u, v) \in v_{\text{candidate}}$ do \}
25: \begin{align*}
    \text{CoV}(u, v) &= \text{CalcCov}(x^n), n \in [1, N] \\
    \text{end for}
\end{align*}
26: \begin{align*}
    v_{ch} &= \text{DescendingSort} (\text{CoV}(u, v), (u, v)) \\
    \text{end for}
\end{align*}
27: \begin{align*}
    v_{\text{temp}} &= \{v_{ch}, ch \in [1, C]\} \\
    v_T &= \text{CommonTop}(v_{\text{temp}}, \text{TopN})
\end{align*}
28: return $v_T$
29: end Function

Using the metrics above, we regard our poisoning attack as a successful attack if it satisfies the following points: 1) The CDP of the backdoored model is similar to the original clean model, which means that our attack has little impact on the original performance. 2) The ASR of the backdoored model can meet our expectations, i.e., the model can achieve an ASR higher than 90%. 3) The backdoored model’s PSNR and SSIM are relatively high, which means that our triggers have no significant effect on the original images, i.e., it is difficult for humans to perceive the presence of our triggers. 4) The state-of-the-art defense work does not defend well against our attack, i.e., after applying the defenses, either the ASR of the backdoored model remains relatively high, or the CDP drops significantly together with the ASR.

Platform. All our experiments are conducted on a server running 64-bit Ubuntu 20.04.3 system with Intel(R) Xeon(R) Platinum 8268 CPU @ 2.90GHz, 188GB memory, 20TB hard drive, and one Nvidia GeForce RTX 3090 GPUs with 24GB memory.

4.2 Effectiveness

4.2.1 Baseline Performance.
For the scenario of self-supervised learning, we train clean DNN encoders (i.e., ResNet-18) on CIFAR-10 using two self-supervised methods (i.e., SimCLR and MoCo V2). And then use the encoder to train downstream classifiers on CIFAR-10, STL-10, and GTSRB tasks. We evaluate their performance in several aspects as the baseline in Table 1. Moreover, for supervised learning, we train clean ResNet-18 models on CIFAR-10 and STL-10, and the effectiveness is shown in Table 2. As we can see from the two tables, the clean models achieve similar performance as those shown in [6, 7, 17]. In addition, the
We evaluate our backdoor attack on the same tasks as those shown in Table 5, we compare the invisibility with state-of-the-art backdoor attacks. We choose four widely used defenses in different types that are most relevant to our attack to evaluate the robustness of our attack. For frequencies, we select triggers with lower and higher frequencies and set proper intensities for them to ensure the ASR is larger than 85% and CDP is around 90%. As shown in Table 7, trigger with larger intensities is easier to achieve backdoor attack (i.e., the ASR is larger), but it loses its stealthiness at the same time (i.e., the PSNR and SSIM get lower). We choose four widely used defenses in different types that are most relevant to our attack to evaluate the robustness of our attack. For frequencies, we select triggers with lower and higher frequencies and set proper intensities for them to ensure the ASR is larger than 85% and CDP is around 90%. As shown in Table 7, trigger with larger intensities is easier to achieve backdoor attack (i.e., the ASR is larger), but it loses its stealthiness at the same time (i.e., the PSNR and SSIM get lower).

### 4.3 Impacts of Intensities and Frequencies

**Impacts of intensities.** To evaluate the influence of intensities, we choose triggers with lower and higher intensities than our trigger, and then inject them into the CIFAR-10 dataset. As shown in Table 7, trigger with larger intensities is easier to achieve backdoor attack (i.e., the ASR is larger), but it loses its stealthiness at the same time (i.e., the PSNR and SSIM get lower).

**Impacts of frequencies.** For frequencies, we select triggers with lower and higher frequencies and set proper intensities for them to ensure the ASR is larger than 85% and CDP is around 90%. As shown in Table 7, trigger with higher frequencies is easier to be perceived by DNN models and a little stealthier than the trigger selected by our proposed method, but it is more likely to be filtered out by the filters (No.1). On the contrary, trigger with lower frequencies is challenging to learn by DNN models, so we need to set slightly higher intensities, which may cause visible changes to the images in the spatial domain and affect the performance of the clean dataset (No.3).

### 4.4 Resistance

We choose four widely used defenses in different types that are most relevant to our attack to evaluate the robustness of our attack, including the detection of training data (i.e., Activation Clustering), the preprocessing of inputs (i.e., Filtering), the detection of inputs (i.e., SentiNet) and the detection of models (i.e., Neural Cleanse).

#### 4.4.1 Resistance to Activation Clustering

Activation Clustering is an outlier detection method commonly used to detect poisoned data since a poisoned input may make the distribution of activations different from a clean input, which amplifies signals critical for classification to be detected by clustering. However, Activation Clustering can only operate on the samples with target labels, so it is not suitable in the scenario of self-supervised learning. We evaluate the backdoored ResNet-18 model trained on our poisoned CIFAR-10 dataset for supervised learning. For the samples with the target label, the FPR (i.e., the ratio of clean samples that Activation Clustering misclassifies to be poisoned samples) is 100.00%, and the FNR (i.e., the ratio of poisoned samples that the method regards as benign samples) is 56.64%. The results show that although many poisoned samples are successfully detected, all the benign samples are also classified to be malicious, which leads to a significant performance drop in the DNN models trained on the dataset processed, and the backdoor can still be injected because the samples with the target label left are all poisoned. In addition, nearly half of the poisoned samples are classified as benign, which means that the activation difference between benign and poisoned samples is not significant, implying the high stealthiness of our backdoor attack.
Table 7: Evaluation of different intensities settings.

| No. | itenities          | PSNR  | SSIM   | CDP   | ASR    | ASR after Filter |
|-----|--------------------|-------|--------|-------|--------|------------------|
| 1   | (60,60,70),(55,55,55),(55,55,55) | 25.03 | 0.9122 | 91.00%| 87.84% | 79.80%           |
| 2 (ours) | (70,70,80),(65,65,65),(65,65,65) | 24.11 | 0.9024 | 90.63%| 91.00% | 86.12%           |
| 3   | (80,80,90),(75,75,75),(75,75,75) | 23.23 | 0.8911 | 90.77%| 91.62% | 78.80%           |

Note: The intensities increase from No.1 to No.3.

Table 8: Evaluation of different frequencies settings

| No. | frequencies | itenities          | PSNR  | SSIM   | CDP   | ASR    | ASR after Filter |
|-----|-------------|--------------------|-------|--------|-------|--------|------------------|
| 1   | (28,0),(30,0),(31,0) | (40,35,30),(25,25,25),(25,25,25) | 31.20 | 0.9530 | 90.29%| 97.15% | 4.32%           |
| 2 (ours) | (1,10),(1,9),(0,10) | (70,70,80),(65,65,65),(65,65,65) | 24.11 | 0.9024 | 90.63%| 91.00% | 86.12%           |
| 3   | (1,7),(3,6),(5,3) | (95,105,130),(85,85,85),(85,85,85) | 21.57 | 0.8624 | 89.00%| 88.18% | 84.68%           |

Note: The frequencies decrease from No.1 to No.3, and the corresponding intensities increase to ensure ASR is larger than 85% and CDP is around 90%.

Figure 3: Critical Regions Identified by SentiNet. Column a) and c) are the results of clean images, and column b) and d) are the results of the corresponding poisoned images.

4.4.2 Resistance to Filtering.
We evaluate the robustness of our attack to the filters on the backdoored model ResNet-18 that trained on poisoned dataset CIFAR-10 using supervised learning. Before feeding the test samples into the model for prediction, we first pass them through four types of filters (i.e., Gaussian, average, median, and SVD filters). Note that the SVD filter in the frequency domain is used to filter out singular frequencies by analyzing the frequency distribution. The result in Table 6 proves that the ASR of our backdoor attack remains high after filtering, but the performance on the clean data drops significantly, which means our backdoor attack is robust to the processing of filters.

4.4.3 Resistance to SentiNet.
SentiNet is used to detect a potential attack region of an image using Grad-CAM developed for model interpretability and object detection. And then the region can be checked manually to identify poisoned inputs, i.e., samples with a trigger patched. We apply SentiNet to the backdoored ResNet-18 models trained by self-supervised learning using SimCLR to see if the trigger patched on the poisoned CIFAR-10 dataset can be detected. Figure 3 shows the regions identified by SentiNet on several randomly selected samples, where column a) and c) are the results of clean images, column b) and d) are the results of the corresponding poisoned images, from which we can see that SentiNet can only identify a partial area of an image as a critical region, however, our trigger overlaps the whole image. In addition, our trigger truly changes the focus of the model on the image compared to the clean image, but the regions identified on poisoned images are still the significant regions of images that lead DNN models to identify the original images, which means that humans cannot detect our trigger using such method.

4.4.4 Resistance to Neural Cleanse.
Neural Cleanse is the most widely used defense against backdoor attacks by detecting the DNN models. For each label, Neural Cleanse tries to find a potential minimal trigger that can misclassify all samples into this target label, and then use an outlier detection algorithm to choose the trigger that is significantly smaller than the others as the real trigger (i.e., the anomaly index is larger than 2), and the corresponding label is the target label of the backdoor attack. We apply Neural Cleanse to detect our backdoored ResNet-18 model trained on CIFAR-10 using SimCLR. The anomaly index of each label is shown in Figure 4, which shows that none of the anomaly indexes are larger than 2, proving that Neural Cleanse cannot find our frequency trigger.
5 DISCUSSION

In this paper, we propose an invisible backdoor attack using data poisoning. Due to the high stealthiness of our frequency trigger, it can also be used to watermark datasets or DNN models. Firstly, we can release a dataset in which all the samples are patched with our invisible trigger, and our backdoored model trained before will output the target label on any samples, but a new model trained on them will not. Secondly, we can release our backdoored model and then use our trigger to verify the ownership of the model. Besides, since the frequency domain is derived from signal processing, our idea of the backdoor attack (i.e., based on some statistic analysis in the frequency domain) may be able to migrate to the speech domain as well.

6 CONCLUSION

In this paper, we propose a generalized backdoor attack approach based on the frequency domain, where the DNN models trained on our poisoned dataset will be implanted with a backdoor without out mislabeling the poisoned samples and accessing the training process. We evaluate our approach in the no-label and clean-label cases on popular benchmark datasets with self-supervised learning and supervised learning and test the effectiveness of the current defenses against the backdoor attack. The results show that our approach can achieve a high attack success rate on all the tasks without significant performance downgrade on the main tasks, and also, it can evade the commonly used defense methods.

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