CROSS-REPRESENTATION TRANSFERABILITY OF ADVERSARIAL PERTURBATIONS: FROM SPECTROGRAMS TO AUDIO WAVEFORMS

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ABSTRACT

This paper shows the susceptibility of spectrogram-based audio classifiers to adversarial attacks and the transferability of such attacks to audio waveforms. Some commonly adversarial attacks to images have been applied to Mel-frequency and short-time Fourier transform spectrograms and such perturbed spectrograms are able to fool a 2D convolutional neural network (CNN) for music genre classification with a high fooling rate and high confidence. Such attacks produce perturbed spectrograms that are visually imperceptible by humans. Experimental results on a dataset of western music have shown that the 2D CNN achieves up to 81.87% of mean accuracy on legitimate examples and such a performance drops to 12.09% on adversarial examples. Furthermore, the audio signals reconstructed from the adversarial spectrograms produce audio waveforms that perceptually resemble the legitimate audio.

Index Terms— adversarial audio attacks, transferability, audio reconstruction.

1. INTRODUCTION

Music genre classification has always been a challenging task for humans [12][3]. The subjectivity and unclear boundaries between genres, added to the uniqueness of artists, makes the classification task very complicated. Yet, well-classifying music is of great interest to many researchers and companies in the entertainment and arts industry. In the last years, convolutional neural networks (CNNs) became increasingly popular due to their high accuracy and performance on image datasets. Therefore, the focus in academia has been on 2D CNNs. In the realms of audio and music processing, CNNs have had a significant impact on several tasks such as automatic music tagging [4], video clip classification based on audio information [5], speaker identification [6], environmental sound classification [7][8][9] and music genre classification [10].

Even if audio is a 1D signal, it is a common practice to use 2D representations, like spectrograms, when training machine learning models. Due to their ability to model the human peripheral auditory system [11], Mel-Frequency Cepstrum Coefficient (MFCC) features are currently used for several audio processing tasks such as music genre classification [12]. Mel-Frequency (MF) spectrograms, which are derived from MFCCs, are one of the most preferred input types for music information retrieval [13]. One of the main advantages of using 2D representations is that they summarize high dimensional waveforms into compact time-frequency representations while audio signals alone are noisier [14]. Regardless of the type of spectrogram; as they are 2D representations of audio signals, they can be treated as images. Therefore, this opens up the opportunity to profit from the recent advances of deep neural networks in computer vision.

Recent works have exploited the capability of CNNs to learn representations directly from spectrograms. Boddapati et al. [15] use short-time Fourier transform (STFT), MFCC and Cross Recurrence Plot (CRP) spectrograms with two different 2D CNN architectures (AlexNet and GoogLeNet) to classify 2D representations of environmental sounds. Lee et al. [16] use 2D CNNs with MF spectrograms as input for music auto-tagging. Pons et al. [17] use 40 bands MF spectrograms to experiment with musically motivated CNNs and try understanding what CNNs learn from particular datasets. Pons et al. [18] use MF spectrograms as input for a randomly weighted CNN for music audio classification. Oramas et al. [19] use constant-Q transform (CQT) spectrograms in their audio-based approach for multi-label music genre classification.

Despite all advantages, it has been shown that approaches based on 2D representations are susceptible to adversarial attacks, which can easily fool these models and raise safety concerns. Esmailpour et al. [20] have shown that the majority of state-of-the-art approaches for audio classification relying on 2D CNNs can be easily deceived, with fooling rates higher than 90% and high confidence. 1D CNNs can also be easily fooled by adversarial attacks. Abdoli et al. [21] demonstrated the existence of universal adversarial perturbations that can fool several audio processing architectures with attack success rates between 91.1% and 74.7%, and signal-to-noise ratio (SNR) between 15.70 dB and 19.62 dB. Du et al. [22] proposed a method based on Particle Swarm Optimization (PSO) for generating adversarial audio for end-to-end audio systems. They evaluated their attacks on a range of applications like speech command recognition, speaker recognition, sound event detection and music genre classification. The proposed attack achieved a success rate of 89.30% on a 1D CNN and 91.20% on a convolutional recurrent neural network with SNR of 15.39 dB and 17.24 dB respectively.

Our contribution in this paper is threefold. Firstly, we present an end-to-end 2D CNN that achieves between 81.87% and 75.84% of mean accuracy in music genre classification, depending on the type of spectrogram. Secondly, we verify the robustness of such model against adversarial attacks and point out a downside of using STFT and MF spectrograms as input for 2D CNNs music classifiers. Finally, we show that attacked spectrograms can be used to reconstruct the audio waveform and that such reconstructed signals are perceptually similar to the legitimate ones, as the perturbations added to the signals are not perceived by most people.

This paper is organized as follows. Section 2 presents the proposed 2D CNN architecture for music genre classification. Section 3 presents a description of the adversarial attacks and the reconstruction of the audio waveforms from spectrograms. Section 4 presents the dataset, the experimental protocol and the results. We compare the performance of the 2D CNN model when using MF and STFT
spectrograms and the vulnerability of such a model to adversarial examples. We also evaluate the transferability of adversarial perturbations from 2D representations to the audio waveform. Finally, the conclusions and perspectives of future work are presented in the last section.

2. PROPOSED 2D CNN ARCHITECTURE

The aim of the proposed end-to-end architecture is to deal with 2D representations of audio signals of various lengths, learning meaningful representations directly from spectrograms. First, we split each audio waveform into fixed-length segments using a sliding window of appropriate width. The window width depends mainly on the signal sampling rate, which in the case of the music dataset evaluated in this paper is 22,050 Hz. In our approach, we use a window of five seconds (110,250 samples) because such a length provides the best trade-off between the number of segments and accuracy. Furthermore, there is also a certain percentage of overlapping between successive audio segments, which aim is to maximize the use of information. In our approach we use 75% overlapping because such an overlapping also provides the best trade-off between the number of segments and accuracy. Furthermore, the overlapping can be viewed as some sort of data augmentation because it naturally increases the number of samples as some parts of the audio signal are reused. Fig. 1 summarizes the process of splitting the audio signal into appropriate segments by the sliding window, which are used as input to the 2D CNN.

During the classification step, since the input audio waveform is split into several segments, we need to aggregate the 2D CNN predictions to come up to a final decision on the input audio, as illustrated in Fig. 1. For such an aim, we used majority vote and the sum rule [9]. When there are $K$ classes, we generate $K$ values and we choose the class with the maximum $y_i$ value as our final prediction.

3. ADVERSARIAL ATTACKS AND AUDIO RECONSTRUCTION

Adversarial attacks can be considered as small crafted perturbations that, when intentionally added to a legitimate example, lead machine learning models to misbehave [23]. Considering $x$ as a legitimate example, then an adversarial example $x'$ can be crafted in such a way that:

$$x \approx x', \quad f^*(x) \neq f^*(x')$$

(1)

where $f^*$ is the post-activation function. Assuming that $x$ is a spectrogram, the crafted $x'$ should be unrecognizable by human visual system.

STFT and MF are the main approaches for producing spectrograms for music signals. To generate the STFT and MF spectrograms, we use a fast Fourier transform (FFT) window of length 512 and 256 samples between successive frames. For the MF spectrograms we use 64 Mel filters. Therefore, the spectrogram dimension is $431 \times 257$ and $431 \times 64$ for STFT and MF respectively. The architecture of the 2D CNN is the same for both input formats. The breakdown of its layers is fully described in Table 1.

| Layer Type | # Filter | Filter Size | Stride | Output Shape |
|------------|----------|-------------|--------|--------------|
| Input      | -        | -           | -      | 257, 431, 1  |
| Conv2D     | 32       | 3, 3        | 1, 1   | 255, 429, 32 |
| Conv2D     | 32       | 3, 3        | 1, 1   | 253, 427, 32 |
| MaxPool    | -        | -           | 2, 2   | 126, 213, 32 |
| Conv2D     | 64       | 3, 3        | 1, 1   | 124, 211, 64 |
| Conv2D     | 64       | 3, 3        | 1, 1   | 122, 209, 64 |
| MaxPool    | -        | -           | 2, 2   | 60, 103, 64  |
| Dense      | -        | -           | -      | -            |
| Output     | -        | -           | -      | 10, 10       |

Table 1. Architecture of the proposed 2D CNN

Moreover, the length of the original audio (before being split) has a direct impact on the number of samples being tested and trained, which may impact the computational cost of the model. The GTZAN dataset has a sampling rate of 22,050 Hz and all original audio files are 30 seconds long.

Fig. 2. Overview of the adversarial attack and audio waveform reconstruction.

Among the several algorithms for generating $x'$, the Fast Gradient Sign Method (FGSM) [24] was one of the first attacks, which still
remains one of the most effective adversarial attacks. Goodfellow et al. [24] introduced the FGSM for generating simple adversarial samples. The method consists of adding to the original image an imperceptibly small vector, whose elements are equal to the sign of the elements of the gradient of the cost function with respect to the input. This vector creates a small perturbation to the target image, which cannot be seen by the human eye and effortlessly deceives CNNs. Kurakin et al. [25] introduced a straightforward way of extending the FGSM method by applying it multiple times with a small step size. Known as the Basic Iterative Method (BIM), this adversarial attack is also able to fool complex CNNs. As illustrated in the upper part of Fig. 3, both adversarial attacks are white-box attacks which means that both the trained CNN and the training dataset should be accessible to fetch its gradient information and generate the adversarial input $x'$ with unrecognizable differences to the legitimate input $x$. The perturbed spectrogram can perhaps make the CNN predict a wrong label with high confidence.

![Original STFT spectrogram vs. FGSM perturbation](image)

Fig. 3. Generating an adversarial example for an STFT spectrogram using the FGSM attack.

![Fig. 3](image)

Fig. 3 shows an example of a legitimate STFT spectrogram attacked with a perturbation produced by the FGSM attack. Such a figure summarizes what happens with all attacked STFT and MF spectrograms, the difference between the adversarial and legitimate spectrograms is imperceptible by the human eye. However, what happens with the perturbed signal in its original representation space, that is, audio waveform? Is such a perturbation remain unperceived by the human auditory system?

### 3.1. Audio Reconstruction

The last contribution of this paper is to evaluate if after performing adversarial attacks to the 2D representations and successfully fooling the 2D CNN, such attacks could be transferred to the 1D signal audio waveform. If so, the perturbations should not be perceptible by human auditory system on the audio after reconstructing it from the perturbed spectrogram.

For such an aim, we need to reconstruct the audio signal from a spectrogram. As the spectrogram does not contain information about the phase of the signal that it represents, it is not possible to reverse the process. However, we can retain the phase information separately and, depending on the type of spectrogram, we can use it to reconstruct the original audio signal, which is the case of the STFT spectrogram. However, to reconstruct the audio signals from the MF spectrograms, it is necessary to estimate the unknown phases iteratively using the Griffin-Lim (GL) algorithm [26].

### 4. EXPERIMENTAL RESULTS

The proposed end-to-end 2D CNN for music genre classification was evaluated on the GTZAN dataset. This data-set consists of 1,000 audio clips of songs, each 30 seconds long. The audio clips are divided in 10 classes and the number of samples in each class are: “Blues: 100”, “Classical: 100”, “Country: 100”, “Disco: 100”, “Hip-hop: 100”, “Jazz: 100”, “Metal: 100”, “Pop: 100”, “Reggae: 100” and “Rock: 100”. The files were collected from a variety of sources in order to represent a variety of recording conditions [27].

The 1,000 audio files were shuffled and divided into three folds with 340, 330 and 330 samples, respectively. Fold 1 contains 34 tracks of each of the 10 genres; Folds 2 and 3 contain 33 tracks of each genre. Every track of every fold was split into 21 short segments according to the sliding window described in Fig. 2. The next step was to generate spectrograms of all 21,000 audio segments. The model was first accessed with MF spectrograms and then STFT spectrograms. Two folds were used for training and 20% of the training set was used for validation. The third fold was used for testing. After predicting the music genre for each segment on the testing set, the predictions for all 21 windows belonging to the same song are averaged to represent a variety of recording conditions [27].

Table 2 shows the results of the FGSM and BIM against the 2D CNN. We evaluate the mean accuracy achieved by the model on the perturbed spectrograms. For both STFT and MF spectrograms the BIM attack is more successful due to its iterative nature. For instance, considering the best result of Table 2, the mean accuracy drops from 81.87% on the legitimate examples to 12.09% on the examples attacked by BIM.

Table 3 shows the results of the FGSM and BIM against the 2D CNN and MF spectrograms with FGSM and BIM adversarial attacks. After testing the 2D CNN against the adversarial samples, fooling rates higher than 80% were achieved for both input types. However, an open question is if such a perturbation added to the spectrogram will remain unrecognizable by human auditory system if the audio waveform is reconstructed from the adversarial spectrogram.

As illustrated in Fig. 2, we reconstruct the audio waveforms from the perturbed spectrograms and evaluate the impact of such a perturbation both perceptually and objectively. Signal-to-noise ratio (SNR) is used as a metric to measure the level of the noise with
respect to the original signal. This metric has been used by previous works to evaluate the quality of the generated adversarial audio by measuring the level of the perturbation on the signal after adding the perturbations \[21, 28, 22\] and it is defined as:

\[
\text{SNR}_{\text{ad}}(x, v) = 20 \log_{10} \frac{P(x)}{P(v)}
\]

where \(x\) denotes the audio reconstructed from the legitimate spectrogram and \(v\) denotes the adversarial noise. \(P(.)\) is the power of the signal or noise, which is defined as:

\[
P(x) = \sqrt{\frac{1}{N} \sum_{n=1}^{N} x_n^2},
\]

where \(x_n\) denotes the \(n\)-th component of the signal \(x\). A high SNR indicates that a low level of noise is added to the audio signal by the adversarial perturbation.

Table 4 shows the mean SNR achieved on the reconstructed audio from the spectrograms attacked by FGSM and BIM. According to Du et al. \[22\], the imperceptible noise requires \(\text{SNR}_{\text{ad}}\) equal or greater than 20 dB. Therefore, the reconstructed audios can be considered as adversarial ones. Furthermore, the reconstructed adversarial audios are indistinguishable from their legitimate counterparts to human perception. Several samples of legitimate and adversarial audios are available to the readers.

| Input                          | Attack | SNR_{ad}(x, v) ± SD |
|--------------------------------|--------|---------------------|
| Audio Reconstructed (STFT)     | FGSM   | 27.76±1.72          |
|                                | BIM    | 15.68±2.59          |
| Audio Reconstructed (MF)       | FGSM   | 23.26±0.22          |
|                                | BIM    | 23.63±0.24          |

5. CONCLUSION

This paper presented an end-to-end approach for music genre classification based on 2D CNNs and evaluated it with two 2D representations: MF spectrograms and STFT spectrograms. The proposed approach learns from spectrograms of audio segments and performs relatively well compared to state-of-the-art approaches on the GTZAN dataset. The proposed 2D CNN achieved 81.87% and 75.84% of mean accuracy for MF and STFT spectrograms, respectively. Even if spectrograms seem to be advantageous to model in a compact and informative way the spectrum of frequencies of a signal as it varies with time, such a 2D representation may not be the safest one when it comes to robustness against adversarial attacks.

In this paper we have shown that the adversarial attacks to the 2D representation of audio signals are visually imperceptible on spectrogram images and they can be easily transferred to the audio waveform while remaining imperceptible. Therefore, there is no human audible or visual way of detecting an adversarial example. The audio signals reconstructed from STFT spectrograms using the phase information have a very high SNR and the adversarial audio reconstructed from such spectrograms also have a SNR greater than 20 dB, what makes impossible for humans to hear the difference between legitimate and adversarial audio examples. Even if the audio signals reconstructed from MF spectrograms do not have SNRs as high as those achieved using STFT spectrograms, the adversarial audio reconstructed from MF spectrograms still have a SNR greater than 20 dB.

Future work on this subject would include assessing the reliability of 1D models on the adversarial attacks originally designed for image samples and transferred to audio signals. The main focus of future research would be exposing the vulnerability of 1D CNN architectures such as those described by Abdoli et al. \[9, 21\] to the adversarial audios resulting in this work.

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