System Fingerprints Detection for DeepFake Audio: An Initial Dataset and Investigation

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ABSTRACT
Many effective attempts have been made for deepfake audio de-
tection. However, they can only distinguish between real and fake. For many practical application scenarios, what tool or algorithm generated the deepfake audio also is needed. This raises a question: ‘Can we detect the system fingerprints of deepfake audio?’ Therefore, this paper conducts a preliminary investigation to detect system fingerprints of deepfake audio. Experiments are conducted on deepfake audio datasets from five latest deep-learning speech synthesis systems. The results show that LFCC features are relatively more suitable for system fingerprints detection. Moreover, the ResNet achieves the best detection results among LCNN and x-vector based models. The t-SNE visualization shows that different speech synthesis systems generate distinct system fingerprints.

CCS CONCEPTS
• Applied computing → System forensics.

KEYWORDS
deefake audio; system fingerprints detection; audio forensics; initial investigation

1 INTRODUCTION
With the application of deep learning technology, audio deepfake techniques [1] [2] [3] [4] [5] are now becoming increasingly ma-
ture. Deepfake audio generated by speech synthesis [6] [7] or voice conversion [8] [9] can already be very similar to the real audio. Deepfake audio can influence hundreds of millions of users by spreading explosively through social multimedia. If used for un-
desirable purposes such as misleading public opinion or attacking identification systems, it would pose a serious threat to global social stability. Therefore, deepfake audio detection has great significance.

Many methods have been proposed to distinguish between real and fake audio with remarkable results. For instance, there are many competitions in the deepfake audio field in recent years. The first ASVspoof challenge, ASVspoof 2015 [10] distinguishes between real speech and spoofing speech. Spoofing speech is synthesized using speech synthesis or voice conversion. The ASVspoof 2017 [11] challenge focuses on replay spoofing attacks detection. The ASVspoof 2019 challenge [12] extends the previous challenges for three major attack types. Building on several previous challenges, ASVspoof 2021 [13] adds a new deepfake audio task. In addition to that, ADD 2022 [14] initiates the first audio deep synthesis detection challenge for more challenging realistic scenarios. Like these challenges, most of the detection work on deepfake audio [16] [17] [18] [19] [20] focus on two aspects: the optimization
of acoustic features and classification models. Davis et al. [21] propose mel-frequency cepstral coefficients (MFCCs) that considered the characteristics of human hearing. Todisco et al. [22] apply constant Q cepstral coefficients (CQCCs) to deepfake audio detection, using constant Q-transform instead of short-time fourier transform to process speech signals. Its performance was better than MFCC. Sahidullah et al. [23] propose linear frequency cepstrum coefficients (LFCCs), which replace Mel scale filters with linear filters. LFCC has better distinguishability in the high-frequency region.

An effective classification model also plays an important role. The gaussian mixture model (GMM) is the traditional classification model. The later emergence of convolutional neural networks (CNNs) [24] has achieved further performance improvements. As a baseline for ASVspoof challenge, the lightweight convolutional neural network (LCNN) [16] is used widely in the field of deepfake audio detection. LCNN can not only separate noise and information signals but also can select features through competitive learning. Residual network (ResNet) [25] alleviates the problem of gradient disappearance in deep CNNs.

All of the above work has made many contributions to fake audio detection. LFCC feature and ResNet model have better performance in fake audio detection. But all these attempts focus on only two types of audio: real and fake. These attempts detect fake audio by learning the differences between real and fake audio. For fake audio, there is no further detection and analysis work.

However, in many practical application scenarios, such as judicial forensics by Public Security Bureau or Court, not only do they care about the authenticity of the audio itself, but also need to know what tool or algorithm generated it. That is, if the audio is detected as deepfake audio, we also want to know which tool generated it. For example, deepfake audio is from Baidu Ai Cloud. This poses a new challenge: deepfake audio forensics. Deepfake audio forensics has great significance and realistic demand. Audio forensic analysis is used to determine the authenticity and verify the integrity of the evidence submitted to court involving civil or criminal proceedings. Moreover, further forensic analysis of deepfake algorithms can also promote better detection techniques in this field and reduce the potential harm and abuse of deepfake audio. Therefore, it is crucial to find effective ways to detect which tool generated the fake audio.

These motivate our further research in the field of deepfake audio detection. These raises a question: ‘Can we detect the system fingerprints of deepfake audio?’ To solve this problem, this paper initially focuses on an investigation for detecting system fingerprints of deepfake audio. In this paper, system fingerprints are different characteristics of audio from different companies’ speech synthesis systems. The detection system finally predicts what tools synthesize deepfake audio, i.e., which speech synthesis system it belongs to. Under different feature input conditions, the different system fingerprints show excellent distinguishability among different models. The experimental results show that the model using LFCC features perform best among all features in the experiment and the ResNet model achieved the highest detection rate. We explicitly visualize the system fingerprints in the deepfake audio to better explain the validity of the forensics, as shown in Figure 1.
The main contributions of this paper are as follows.

- To the best of our knowledge, we propose the concept of system fingerprints for the first time, and analyze the safety significance of system fingerprints.
- We research on how to detect system fingerprints and analyze the differences in fingerprints of different speech synthesis systems.
- We have a deep discussion on the existing limitations of the current system fingerprints detection methods, and what aspects are worth further research in the future.

The rest of the paper is organized as follows. Section 2 introduces related work and Section 3 explains our countermeasures for detecting system fingerprints. Section 4 gives the evaluation metrics. Besides, experiments and discussion are reported in Section 5 and Section 6 respectively. Finally the conclusions are given in Section 7, and some directions for future research are provided.

2 RELATED WORK

In the audio field. There have been some early attempts[26] [27] [28] [29] [50] about audio fingerprints. Pedro Cano et al. [31] introduce concepts related to audio fingerprints, as well as some possible usage scenarios and application contexts. Dominic Milano et al. [32] explain how digital fingerprints of audio might work. Peter Grosche et al. [33] propose that the same piece of music can be recognized in different performance environments based on the audio fingerprints. Jaap Haitsma et al. [34] introduce a very effective fingerprints search strategy. The search can be achieved by matching audio fingerprints in the music library. Dajiang Chen et al. [35] propose a method for device authentication using the frequency response of speakers and microphones as acoustic hardware fingerprints, etc. Peter Jan O Doet et al. [36] find differences in the fingerprints after audio compression, and comparatively studied the compressed versions of the fingerprints. In the audio field, these attempts are aimed at the traditional detection methods of real audio fingerprints, such as music recognition, and acoustic hardware fingerprints detection.

In the image field, Yu et al. proposed learning GAN fingerprints [37] towards image attribution. GAN fingerprints show that any single difference in training sets, or even initialization seeds can result in the distinct differences. Yu et al. [38] embed artificial fingerprints into training data then discovered the transferability of such fingerprints from training data to the generated deepfake images. These studies are aimed at the rapid development of image fingerprints generation models and detection countermeasure techniques.

They have both made many contributions to the field of fingerprints detection. Different from this paper, this paper presents the first work at system fingerprints detection of deepfake audio.

3 FORENSICS COUNTERMEASURES

Previous attempts show that LFCC features and the ResNet model are promising for many tasks. Therefore, this paper uses the ResNet model with LFCC features to detect system fingerprints of deepfake audio. The proposed model architecture is shown in Figure 2. It is composed of a feature extractor and a system fingerprints discriminator.

3.1 Feature input

The input Linear frequency cepstral coefficients (LFCCs) [23] are cepstrum features based on triangular filter banks. Instead of conventional mel filter banks, LFCC utilizes linear filter banks to process speech signals. LFCC is widely used not only in the deepfake audio detection, but also used in the ASVspoof challenge [12] [13]. The feature extraction process is as follows. First, pre-processing operations are performed on the audio, including pre-emphasis, framing, and windowing. Then for each short-time analysis window, the corresponding spectrum is obtained by FFT; the spectrum is passed through a linear filter set to obtain a linear spectrum. Finally, cepstrum analysis is performed on top of the linear spectrum to obtain LFCC. After extracting features, We input features to the system fingerprints discriminator.

3.2 Model architecture

In our work, We use ResNet as our system fingerprints detection model in our experiments. It is well known that the depth of a network is a factor in determining its performance. However, due to the infamous gradient disappearance problem, as the network model gets deeper, the learning of the model becomes worse. ResNet proposes a residual module that addresses the problem of network “degradation”. ResNet allows deeper networks to be trained, resulting in models that typically perform better.

ResNet introduces a shortcut connection that allows the gradient to flow through a large number of layers. In our experiments, we use a residual network with eight basic blocks, as shown in Figure 2(b). We use a two-layer structure for each basic block. The structure of each basic block is shown in Figure 2(c). We consider a basic block to be defined as:

\[ y = F(x, \{W_i\}) + x \]  \hspace{1cm} (1)

Here \( x \) and \( y \) represent the input and output vectors. \( F(x, \{W_i\}) \) represents the residual mapping to be learned. When changing the input/output channels, a linear projection \( W_s \) can be used to match the dimensions:

\[ y = F(x, \{W_i\}) + W_s x \]  \hspace{1cm} (2)

If \( H(x) \) represents an underlying mapping. According to equation 2, in the case where the input and output have the same dimension, multiple nonlinear layers can asymptotically approximate the residual functions, i.e., \( H(x) = x \). For \( F(x) = H(x) - x \), we let these layers approximate a residual function \( F(x) \). Thus, the original mapping to be learned becomes \( F(x) = x \).

ResNet-18 consists of layers in the following order: 7×7 convolutional layers, maxpool layer, four residual blocks, global average pooling layer, followed by a fully connected layer. Then a fully connected layer inputs the embeddings to a system fingerprints discriminator. Finally, multiple output heads correspond to five speech synthesis system categories: AISpeech, Sougou, Alibaba Cloud, Baidu Ai Cloud, and Databaker Technology. During the training process, we use cross-entropy (CE) loss to help the model optimize.
4 EVALUATION METRICS

The performance of our forensic countermeasures is evaluated via Precision, Recall and $F_1$ – score. In detection problems, systems are designed to decide whether a given event or feature is present or absent in a given space. Given a ground-truth annotation, the ideal system behavior is to detect all possible entities without giving any false alarms. Quantifying a system performance is normally done by combining True/False Positives/Negatives to measure the Precision and Recall. Precision and Recall are defined by:

$$
\text{Precision} = \frac{TP}{TP + FP} \quad (3)
$$

$$
\text{Recall} = \frac{TP}{TP + FN} \quad (4)
$$

where $TP$, $FP$ and $FN$ denote the true positive, false positive, false negative, respectively. And $F_1$ – score is defined as follow.

$$
F_1 - \text{score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (5)
$$

The $F_1$ – score is given by the harmonic mean between Precision and Recall.

5 EXPERIMENTS

5.1 Datasets

The datasets include 83,129 training audio, 26,040 development audio, and 26,040 test audio. All the datasets come from five speech synthesis systems: AISpeech, Sougou, Alibaba Cloud, Baidu Ai Cloud, Databaker Technology. The systems composition of each section of the datasets is shown in Table 1. The datasets construction and experimental results in this paper are only for scientific research purposes. To protect the privacy of each company, we use A, B, C, D, and E to represent the five speech synthesis systems, and the five alphabetical order in this paper has no other meaning. Different companies represent different deepfake audio generated methods. The overall composition of the datasets is shown in Table 2. The datasets consist of a total of 136 speakers, of which the training set consists of 84 speakers, and the development set and the test set consist of 26 speakers respectively. The genders consist of male, female, child male, child female. There was no overlap of all speakers between the three datasets, and the proportion of every gender is balanced. All deepfake audio is mono, 16000Hz sampling rate.

1https://www.aispeech.com
2https://ai.sogou.com
3https://cn.aliyun.com
4https://ai.baidu.com/tech/speech/tts
5https://www.data-baker.com
Table 1: The systems composition of each section of the dataset

|        | A | B | C | D | E |
|--------|---|---|---|---|---|
| Train  | #Utterances | 26026 | 10009 | 30060 | 7014 | 10020 |
|        | #Genders   | 3    | 3    | 3   | 2   | 2    |
|        | #Speakers  | 26   | 10   | 31  | 7   | 10   |
| Development | #Utterances | 8008 | 4004 | 10020 | 2004 | 2004 |
|        | #Genders   | 2    | 4    | 3   | 2   | 2    |
|        | #Speakers  | 8    | 4    | 10  | 2   | 2    |
| Test   | #Utterances | 11012 | 2002 | 7014 | 2004 | 4008 |
|        | #Genders   | 4    | 2    | 3   | 2   | 2    |
|        | #Speakers  | 11   | 2    | 7   | 2   | 4    |

Table 2: The overall composition of the dataset

|        | Train | Development | Test |
|--------|-------|-------------|------|
| #Utterances | 83129 | 26040       | 26040 |
| #Genders   | 3     | 4           | 4    |
| #Speakers  | 84    | 26          | 26   |

5.2 Experimental setup

Feature extraction: All experiments are implemented on the PyTorch [39] platform. As experimental features, we take three features including MFCC, CQCC, and LFCC. First, the mel-frequency cepstral coefficients (MFCCs) and constant Q cepstral coefficients (CQCCs) are extracted as low-level features, and they are 40-dimensional and 60-dimensional respectively. But they are both non-linear. In addition to that, we extract the 60-dimensional linear frequency cepstral coefficients (LFCCs) of speech, which are then fed into the neural network. For LFCC, the length of the window is set to 25ms. The number of filters is set to 20. The number of FFT bins is set to 512 and frame shift is set to 10ms.

Model architecture: As for the models, we experimented with x-vector, LCNN, and ResNet.

- **x-vector**: x-vector as a baseline system in the field of voiceprint recognition, which is very similar to the goal of our task. We adopted the x-vector recognition system builds on TDNN embedding architecture. The first five layers called frame layers operate at the sequential frame level. At the statistical pooling layer, frame 5 outputs from all frames are aggregated by computing the mean and standard deviation. The subsequent frames operate on this 1024-dimensional vector which represents the entire segment and are named segment layers. Then we extract embeddings at segment 6, the output dimension at this layer is set to 512-dimensional. The extracted embeddings are x-vectors. The last output layer has five output nodes corresponding to five speech synthesis systems.

- **LCNN**: LCNN is widely used in the field of deepfake audio detection and has achieved good results. Therefore, we employed LCNN as a classifier model, a lookup-based convolutional neural network. This deep neural network architecture uses max feature map activation. The max feature map divides the original input layer into two parts and discards the smaller output part by competitive learning, leaving the larger output part. After nine convolutional layers with max feature map, we obtained the hidden features. Hidden features pass through two BLSTM layers and then are summed up. Finally, a classification layer projects the embeddings to multi-classification.

- **ResNet**: The deep residual learning framework has fewer filters and lower complexity. We chose 18-layer ResNet that converges faster. The principle of ResNet is given in detail in Section 3. For each building block, we use a stack of two convolutional layers. We use batch normalization after each convolutional layer, then use the ReLU activation function. The convolutional layers are all with kernels of $3 \times 3$. The subsampling is performed by convolutions with a stride of 2. The network ends with a global average pooling, a fully-connected layer. Finally, the network outputs the classification results of the five speech synthesis systems.

Training strategy: Parameters are initialized randomly. The training was conducted with the Adam optimizer to accelerate optimization by applying adaptive learning rate. The initial learning rate is set to 0.001 for Adam, with linear learning rate decay. These models are trained with a mini-batch size of 256. The num epochs is set up 100.

5.3 What feature is more suitable for detecting system fingerprints?

To verify the effectiveness of LFCC, we conduct three groups of experiments to evaluate its performance of detecting system fingerprints. The overall experimental results are shown in Table 3. We observe that LFCC shows a better performance compared to MFCC, and CQCC.

- $F_1$ score value of LFCC-X-vector is 85.30% (**Precision** value is 85.17% and **Recall** value is 85.58%).

- $F_1$ score value of LFCC-LCNN is 96.88% (**Precision** value is 96.49% and **Recall** value is 97.64%).
Table 3: The results of system fingerprints detection models trained with different features on the test set.

| Features | X-vector | LCNN | ResNet |
|----------|----------|------|--------|
|          | Precision | Recall | $F_1$ - score | Precision | Recall | $F_1$ - score | Precision | Recall | $F_1$ - score |
| MFCC     | 82.63%    | 74.82% | 76.87% | 81.34%    | 80.91% | 81.95% | 81.71% | 81.82% |
| CQCC     | 84.15%    | 82.45% | 83.18% | 82.39%    | 81.44% | 81.47% | 92.27% | 92.83% | 92.50% |
| LFCC     | 85.17%    | 85.58% | 85.30% | 96.49%    | 96.88% | 99.43% | 99.51% | 99.47% |

Table 4: The results of system fingerprints detection models trained using MFCC features on each speech synthesis systems.

| Systems | X-vector | LCNN | ResNet |
|---------|----------|------|--------|
|          | Precision | Recall | $F_1$ - score | Precision | Recall | $F_1$ - score | Precision | Recall | $F_1$ - score |
| A       | 82.16%    | 91.16% | 86.43% | 90.75%    | 91.49% | 96.59% | 94.13% | 95.35% |
| B       | 93.00%    | 99.85% | 96.30% | 99.97%    | 97.86% | 99.83% | 99.95% | 99.89% |
| C       | 86.22%    | 87.92% | 87.06% | 92.88%    | 92.32% | 93.32% | 95.50% | 94.40% |
| D       | 63.39%    | 53.74% | 58.17% | 56.92%    | 60.26% | 59.78% | 60.02% | 60.12% |
| E       | 88.39%    | 41.42% | 56.41% | 53.64%    | 59.75% | 59.18% | 59.46% | 59.73% |
| Total   | 82.63%    | 74.82% | 76.87% | 81.34%    | 80.91% | 81.95% | 81.71% | 81.82% |

Table 5: The results of system fingerprints detection models trained using CQCC features on each speech synthesis systems.

| Systems | X-vector | LCNN | ResNet |
|---------|----------|------|--------|
|          | Precision | Recall | $F_1$ - score | Precision | Recall | $F_1$ - score | Precision | Recall | $F_1$ - score |
| A       | 86.42%    | 95.48% | 90.72% | 99.87%    | 98.15% | 100.00% | 99.47% | 99.74% |
| B       | 99.75%    | 100.00% | 99.88% | 100.00%   | 100.00% | 100.00% | 100.00% | 100.00% |
| C       | 94.80%    | 89.71% | 92.18% | 92.82%    | 96.03% | 98.63% | 99.61% | 99.11% |
| D       | 58.75%    | 52.45% | 55.42% | 48.15%    | 37.78% | 72.92% | 80.34% | 76.45% |
| E       | 81.05%    | 74.60% | 77.69% | 71.12%    | 89.82% | 84.73% | 87.20% | 87.20% |
| Total   | 84.15%    | 82.45% | 83.18% | 82.39%    | 81.47% | 92.27% | 92.83% | 92.50% |

Table 6: The results of system fingerprints detection models trained using LFCC features on each speech synthesis systems.

| Systems | X-vector | LCNN | ResNet |
|---------|----------|------|--------|
|          | Precision | Recall | $F_1$ - score | Precision | Recall | $F_1$ - score | Precision | Recall | $F_1$ - score |
| A       | 96.72%    | 99.43% | 98.06% | 99.21%    | 99.52% | 99.77% | 99.67% | 99.72% |
| B       | 98.19%    | 100.00% | 99.08% | 99.95%    | 99.98% | 100.00% | 100.00% | 100.00% |
| C       | 99.55%    | 94.50% | 96.96% | 99.43%    | 99.18% | 99.43% | 99.08% | 99.25% |
| D       | 52.76%    | 59.68% | 56.01% | 84.10%    | 91.15% | 99.25% | 99.25% | 99.25% |
| E       | 78.63%    | 74.28% | 76.39% | 99.75%    | 94.58% | 98.71% | 99.55% | 99.13% |
| Total   | 85.17%    | 85.58% | 85.30% | 96.49%    | 97.64% | 96.88% | 99.43% | 99.51% |

- $F_1$ - score value of LFCC-ResNet is 99.47% ($Precision$ value is 99.43% and $Recall$ value is 99.51%).

- All three $F_1$ - score values are optimal on three models. For LFCC, the average $F_1$ - score value of the three models is 93.88%. The values exceeded MFCC and CQCC by 14.02% and 8.16% respectively.
The reason for the relatively good performance of the LFCC may be that the audio of the five speech synthesis systems differ more in high frequencies, while LFCC has better resolution in the high-frequency region. As a result, LFCC becomes the relatively more suitable feature for detecting system fingerprints.

5.4 What model architecture is more suitable for detecting system fingerprints?

In addition to that, we use three models to verify the effectiveness of ResNet. The experimental results are shown in Table 3, Table 4, Table 5, Table 6.

- $F_1 - score$ value of MFCC-ResNet is 81.82% ($Precision$ value is 81.95% and $Recall$ value is 81.71%).
- $F_1 - score$ value of CQCC-ResNet is 92.50% ($Precision$ value is 92.27% and $Recall$ value is 92.83%).
- $F_1 - score$ value of LFCC-ResNet is 99.47% ($Precision$ value is 99.43% and $Recall$ value is 99.51%).

ResNet model with three features all get the highest $F_1 - score$. The experimental result of the ResNet model achieved the highest average $F_1 - score$: 91.26%, higher than x-vector and LCNN, which are 81.78% and 86.42% respectively.

The reason for the relatively poor performance of the x-vector may be that the goal of the x-vector focuses on the classification of a large number of speakers. However, this is not very compatible with the goal of this task. Whereas LCNN separates the noisy signals from the informative signals by competitive learning, our dataset does not have a large number of noisy signals.
5.5 Comparison of the performance of five speech synthesis systems:

The detailed performance for detecting system fingerprints of the five speech synthesis systems is shown in Table 4, Table 5, and Table 6. Remarkably, the B speech synthesis system shows the best detection results. System fingerprints of the D speech synthesis system and E speech synthesis system are relatively difficult to detect. Possible reasons for different system fingerprints detection performance are as follows.

As shown in Figure 1, we visualize the distribution of the audio system fingerprints features of the five synthesis systems, and audio system fingerprints features are clustered into five categories. Different colors represent different speech synthesis systems: magenta dots represent Databaker Technology system, green dots represent Baidu Ai Cloud system, yellow dots represent sougou system, blue dots represent Alibaba Cloud system, and red dots represent Aspeech system. Our results show that different speech synthesis systems can result in distinct system fingerprints features for effective attribution.

As shown in Figure 3, these spectrograms are derived from real audio and deepfake audio which is from five speech synthesis systems. The audio generated by different speech synthesis systems is quite different from the real audio. Different from the current work on real-fake binary classification, this paper focuses on learning the differences in deepfake audio and detecting the system fingerprints of deepfake audio. There are significant differences in the speech spectrogram between the five speech synthesis systems. First, the spectrum shows that compared with other speech synthesis systems, system-B lacks a lot of high-frequency information. In addition to this, system-D has higher speech data energy than other audio. The semantic pauses in the audio of each speech synthesis system, referred to as the speech “gaps” in the spectrograms, are quite different. Influencing factors of fingerprints detection of different speech synthesis systems is still an open problem.

6 DISCUSSION

The above experimental results show that system fingerprints exist and system fingerprints detection is effective. However, there are still some limitations in our work, as follows.

- We don’t know what has a greater impact on generating system fingerprints. There are many factors that affect the generation of system fingerprints, such as acoustic models, vocoders in speech synthesis systems, etc. This paper detects the final system fingerprints, but did not know which specific module of speech synthesis system has more impact on the generation of system fingerprints.
- The number of speech synthesis systems for detection is limited. This paper only detects and compares the system fingerprints of five speech synthesis systems. System fingerprints detection for other speech synthesis systems should be studied.
- Our work only detects system fingerprints on the deepfake audio synthesized by seen speech synthesis systems. Although the speakers of the test set are never seen before, the trained models are tested on seen speech synthesis systems.

In many practical scenarios, there are many unseen types of detection requirements. It’s important to detect unseen system fingerprints.

7 CONCLUSIONS

To answer the initial question, 'Can we detect the system fingerprints of deepfake audio?', this paper uses the ResNet model with LFCC features to detect system fingerprints of deepfake audio. We construct deepfake audio datasets from five speech synthesis systems. To verify the effectiveness of the forensic countermeasures, We trained different models with different representative features. The results show that LFCC features are relatively more suitable for system fingerprints detection. Besides, the ResNet achieves the best detection results among LCNN and x-vector based models. We visualize the distinct distribution of fingerprints features of different speech synthesis systems. Future work includes considering improving the above-mentioned limitations.

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