ABSTRACT

With the recent advances in voice synthesis such as WaveNet, AI-synthesized fake voices are indistinguishable to human ears and widely applied for producing realistic and natural DeepFakes which are real threats to everyone. However, effective and robust detectors for synthesized fake voices are still in their infancy and are not ready to fully tackle this emerging threat. In this paper, we devise a novel approach, named DeepSonar, based on monitoring neuron behaviors of speaker recognition (SR) system, a deep neural network (DNN), to discern AI-synthesized fake voices. Layer-wise neuron behaviors provide an important insight to hunt the differences among inputs, which are widely employed for building safety, robust and interpretable DNNs. In this work, we leverage the power of layer-wise neuron activation patterns with a conjecture that they can capture the subtle differences between real and AI-synthesized fake voices and provide a cleaner signal to classifiers than raw inputs. Experiments are conducted in three datasets (including commercial products from Google, Baidu, etc.) containing both English and Chinese languages to corroborate the high detection rates (98.1% average accuracy) and low false alarm rates (0.02 equal error rate) of DeepSonar in discerning fake voices. Furthermore, extensive experiment results show its robustness against manipulation attacks (e.g., voice conversion and additive real-world noises). Our work also poses a new insight into adopting neuron behaviors for effective and robust AI aided multimedia fakes forensics instead of motivated by various artifacts introduced in fakes.

CCS CONCEPTS

- Security and privacy → Human and societal aspects of security and privacy;
- Information systems → Multimedia information systems;
- Computing methodologies → Artificial intelligence.

KEYWORDS

DeepFake, fake voice, neuron behavior

1 INTRODUCTION

In the August 2019, the wall street journal reported a new titled "Fraudsters Used AI to Mimic CEO’s Voice in Unusual Cybercrime Case". In this report, criminals used AI-based software to impersonate a CEO’s voice and successfully swindled more than $243,000 by speaking on the phone in March, 2019. Recently, advances in AI-synthesized techniques have shown its powerful capabilities in creating highly sounded realistic voices \[11, 42\], indistinguishable images \[12, 15, 50\], and natural videos \[3, 13, 43\]. Human eyes and ears could be easily fooled by these realistic DeepFakes \[35, 36\]. Furthermore, producing DeepFakes is easy with free tools like FaceApp, ZAO, etc. Thus, it also raises security and privacy concerns to everyone while we are enjoying the fun of these synthesized fakes. Powerful defense mechanisms should be developed by the community for fighting against DeepFakes and protecting us \[28, 48\].

Voice/speech synthesis steps into a new era since DeepMind developed WaveNet \[9, 38\] which could generate realistic and convincing voices. Improving the interaction experiences between machines and humans is the initial idea for developing voice synthesis techniques. Based on this idea, some commercial products...
like intelligent customer service are created by using voice synthesis techniques. Unfortunately, some criminals misuse them for illegal purposes like a politician gives an unreal statement which may cause a regional crisis or someone imitates the victim’s voice for fraud intentions. All of these can be easily performed without any efforts by merely giving texts and a clip of the victim’s real voice using some open-sourced tools [16] or commercial products such as Baidu text-to-speech (TTS) systems. Thus, discerning a clip of voice is synthesized with AI or spoken by humans is extremely important in the era when hearing is not believing anymore.

TTS synthesis, voice cloning (VC), and replay attack (RA) are three different modalities for synthesizing fake voices [29]. TTS and VC regenerate the content, thus they are more realistic than RA and difficult for human ears to distinguish. Therefore, they are especially worrisome and pose the greatest risks. Figure 1 shows a more detailed description of the two fake voices. Recently, AI-synthesized fake voices have already drawn attention from the community. Google launched a challenge competition dedicated to spoofed voice detection [47]. Farid et al. proposed the first bispectral analysis method to distinguish real human voices and AI-synthesized voices based on the observation of the bispectral artifacts in fake voices [1]. However, existing works on discerning AI-synthesized fake voices are all failed in fully tackling the aforementioned TTS and VC fake voices and thoroughly evaluating their robustness against manipulation attacks, which is extremely important for a detector deployed in the wild. Here, manipulation attacks indicate voices are added with real-world noises (e.g., rain, laughing) or converted by manipulating their signals without altering its linguistic contents, such as resampling, shifting pitch.

Voice synthesis and image synthesis are regularly combined for producing audio-visual consistent video DeepFakes. Compared to image synthesis, voice synthesis exhibits some differences and brings new challenges to detection. Firstly, artifacts in fake voices could be hardly sounded and provide sufficient clues for forensics, which is vastly different from artifacts in fake images that are easily noticed by eyes. Secondly, voice signals are one dimension signals. It is not simple to introduce artifacts into the voice synthesis procedure as in images that have three channels. Lastly, voices recorded indoors or outdoors where noises are abundant, it is easy for attackers to fool detectors by adding real-world noises in such circumstances, thus robustness is essential for fake voice detectors.

In this paper, we propose a novel approach, named DeepSonar\(^2\) as presented in Figure 1, based on monitoring neuron behaviors of a DNN-based SR system with a simple binary-classifier to discern AI-synthesized fake voices. We conjecture that the layer-by-layer neuron behaviors in DNNs could provide more subtle features and cleaner signals to classifiers than raw voice inputs, which served as an important asset for differentiating real human voices and fake voices. In this work, we dedicated to the TTS and VC fake voices since they are AI-synthesized with content regenerated and more indistinguishable than RA to our ears. To the best of our knowledge, this is the first work employing layer-wise neuron behaviors to discern AI-synthesized voices and conducting a comprehensive evaluation on its robustness against two manipulation attacks, 1) voice conversions, and 2) additive real-world noises.

To comprehensively evaluate the effectiveness and robustness of our approach in discerning AI-synthesized fake voices, our experiments are conducted in three datasets including publicly dataset where voices are synthesized with commercial products and self-build dataset with available open-sourced tools. In experiments, we aim to evaluate the effectiveness of DeepSonar in distinguishing fake voices synthesized with different languages, synthetic techniques, etc. and investigate the robustness of DeepSonar in tackling two manipulation attacks (including voice conversion and additive real-world noises). Experimental results have shown that DeepSonar gives an average accuracy higher than 98.1% and an equal error rate (EER) lower than 0.02 in the three datasets. DeepSonar also outperforms prior work leveraging bispectral artifacts to differentiate fake voices [1] in both effectiveness and robustness. Our main contributions are summarized as follows.

- **New observation of layer-wise neuron behaviors for discerning fake voices.** We observe that the layer-wise neuron behaviors capture more subtle features that provide cleaner signals to classifiers than raw voice inputs for building effective and robust fake detectors. Thus, we propose DeepSonar based on this observation by monitoring neuron behaviors to reveal the differences between real voices and AI-synthesized fake voices.
- **Performing a comprehensive evaluation of the effectiveness and robustness against manipulation attacks.** Experiments are conducted in three datasets where voices are synthesized with various techniques, containing English and mandarin Chinese languages are spoken by males and females with different accents. Experimental results illustrated its effectiveness in discerning fake voices and robustness against two manipulation attacks, voice conversions and additive real-world noises.
- **New insight for fighting against AI aided multimedia fakes.** Instead of investigating the artifacts introduced by various synthetic techniques, our approach presents a new insight by leveraging the power of layer-wise neuron behaviors for differentiating real and fake in a generic manner. Furthermore, it also shows the potentials for building robust detectors and evasion manipulation attacks, which is important to be deployed in the wild.

The remainder of our paper is organized as follows. Section 2 discusses the related work. Section 3 presents our method on discerning fake voices in detail. In Section 4, we introduce the experimental settings (e.g., datasets, baselines, and evaluation metrics) and implementation details. We show the experimental results and demonstrate the effectiveness and robustness of our proposed method in Section 5. Finally, Section 6 concludes this paper and discusses the future research directions.

\(^2\)Sonar is known as its powerful capabilities in sniffing and probing electronic devices under water based on sound signals. We hope that our approach is a sonar in discerning AI-synthesized fake voices.

2 RELATED WORK

2.1 Voice Synthesis

Voice synthesis is divided into two categories: 1) non-DNN based such as using Hidden Markov Models (HMMs) and Gaussian Mixture Models (GMMs) to learn speech features and replicate them, and 2) DNN based for synthesizing naturalness speech and even on unseen words.
Non-DNN based. The first technique is speech concatenation that concatenates some pre-recorded speech segments to synthesize a new clip voice [55]. The other technique on format analysis uses acoustic models without a human voice as input to generate robotic-sounding speech [45]. Modeling the human vocal tract and vocal biomechanics is another technique for synthesizing speech, which is known as articulatory speech synthesis [22]. Some studies explore leveraging HMM to modulate speech properties like fundamental frequency and duration [57]. These techniques are widely employed in the early years for synthesizing speech, but they suffer naturalness issues, which could be easily sounded by human ears.

DNN based. DNN-based speech synthesis techniques directly map linguistic features to acoustic features by leveraging the power of DNNs in representation. Various models (e.g., Boltzmann machines [20], deep belief network [14], mixed density networks [2], Bidirectional LSTM [18]) are proposed based on DNNs for synthesizing high quality and naturalness speech. Some synthesized samples are available online [33].

WaveNet [38] developed by DeepMind in 2016 and Tacotron [51] created by Google in 2017 are two milestones in speech synthesis. The two models significantly promote the progress of speech synthesis which enables large scale commercial applications for building TTS and VC systems is possible. WaveNet is originated from PixelCNN [49] or PixelRNN [39] and shown its powerful capabilities in modeling waveforms with a generative model which is trained in a real audio dataset. Tacotron [51] is an end-to-end speech synthesis model that can be trained on <text, audio> pairs to avoid large human annotation efforts.

Due to the powerful capabilities of WaveNet and Tacotron, some commercial products are developed based on them, such as Baidu TTS [27], Microsoft Azure TTS [8], Amazon AWS Polly [5], and Google Cloud TTS [7]. Unfortunately, some attackers maliciously use speech synthesis techniques and develop fake voices for fraud intentions, which brings potential security concerns to us.

2.2 Fake Voice Detection

In the past decades, some digital audio forensic studies are working on detecting various forms of audio spoofing [56]. These approaches examine metadata of audio files and investigate their actual bytes. Douglas et al. [17] examined the eleven audio recordings from three olympus recorders in the digital header data for audio authentication. Malik et al. [58] proposed using acoustic environment signature as an important feature for detecting audio forgery by verifying the integrity of digital audio. These studies failed in addressing audio content that is synthesized. The most similar work to us is [1] which is the first study dedicated to AI-synthesized fake voices. In their work, they proposed a bispectral analysis method for detecting AI-synthesized fake voices. They observed that specific and unusual spectral correlation exhibited in the fake voices synthesized with DNNs, which is called bispectral artifacts. Thus, they explored to use higher-order polyspectral features for discriminating fake voices. This work is also motivated by investigating artifacts introduced in fake voices like some recent studies on detecting synthesized fake images [19, 54].

Artifact-based detectors will be invalid when the artifacts fixed with some optimization methods or new synthetic techniques proposed.

In this paper, instead of investigating the artifacts in raw voices introduced in synthesis, we explore a new way by monitoring neurons behaviors of DNN-based SR systems with a simple binary-classifier to distinguish real and fake voices. The layer-wise neuron behaviors can capture more subtle features in differentiating real and fake voices. Experimental results show that our approach outperforms previous work by investigating bispectral artifacts [1] in both effectiveness and robustness evaluations.

3 METHOD

In this section, we firstly introduce our basic insight by monitoring neuron behaviors to discern AI-synthesized fake voices, and then present the overview framework of our proposed DeepSonar, finally detail how to capture the layer-wise neuron behaviors and detecting fake voices with binary-classifier in the following subsections.

3.1 Insight

Monitoring neuron behaviors is an important technique for hunting the differences among a set of inputs to DNNs and investigating the internal behaviors of DNNs, which is widely employed in assuring the quality of DNNs [23, 30, 40, 53], protecting the safety of DNNs like fighting adversarial examples attack [24, 25], and providing interpretation for DNNs [44], etc.

In assuring the quality of DNNs, both DeepXplore [40] and DeepGauge [23] introduced neuron coverage as testing criteria to explore the amount of DNN logic covered by given a set of inputs. Neuron coverage is similar to code coverage in traditional software testing and used to explore the vulnerabilities of DNNs which is susceptible to adversarial examples [10]. In ensuring the safety of DNNs, NIC [24] and MODE [25] exploited the critical neurons in DNNs for detecting adversarial examples and fixing bugs that are buggy neurons caused misclassification in DNNs. In providing interpretation for DNNs, AMI [44] explored the correlation between important neurons and human perceptible face attributes.

According to recent studies, neuron behaviors have demonstrated their powerful capabilities in investigating the internal behaviors of DNNs and revealing the minor differences among inputs like adversarial examples and legitimate inputs. In this work, we conjecture that layer-wise neuron behaviors could capture more subtle features and produce cleaner signals to a classifier than raw voice inputs in distinguishing the differences between inputs. Thus, we propose DeepSonar by monitoring layer-wise neuron behaviors of the DNN-based SR system with a simple binary-classifier to discern human speeches and AI-synthesized fake voices.

3.2 Overview of DeepSonar Framework

We present the overview of DeepSonar framework in Figure 2. Generally, we first collect numerous real and synthesized fake voices with good diversity in languages, accents, genders, and synthetic techniques. Real voices are collected from public datasets and available free videos from the internet which are spoken by humans in different languages, accents by males or females. In fake voice collection, 1) use TTS techniques to synthesize new voices with merely given texts, 2) utilize VC techniques to produce a clip of fake.
voices having similar timbre to real voices. Then, we adopt a DNN-based SR system to capture the layer-wise neuron behaviors for both real and fake voices and determine the activated neurons with designed neuron coverage criteria. Finally, the captured neuron behaviors are formed as input feature vectors for training a simple supervised binary-classifier based on shallow neural networks to predict whether a clip of voice is a human speech or synthesized.

3.3 Layer-wise Neuron Behaviors

Layer and neuron are the basic components in a DNN model. Each layer in DNNs has its own distinct merits in learning the input representations [26]. A neuron $x$ is the basic unit for representing the inputs in each layer and calculated by activation function $\varphi$, previous layer neurons $X'$, weights matrix $W$, and bias $b$. Specifically, the output value of neuron $x$ is calculated as $\varphi(W \cdot X' + b)$.

Neurons can be classified as activated neurons and inactivated neurons by given an input according to recent studies in DNN testing [40]. Here, an activate neuron means that its output value is larger than a predefined threshold $\delta$, and vice versa. According to recent studies, activated neurons carry more information than inactivate neurons and have a large influence on the following consecutive layers [23, 40]. Thus, we monitor the activated neurons to discern the differences among inputs.

In monitoring the layer-wise neuron behaviors, we need to address the following three issues. Firstly, which DNN-based model is more suitable for monitoring neuron behaviors? Secondly, which layers in the model are elected to monitor neuron behaviors? Lastly, how to determine the threshold $\delta$ using neuron coverage criteria?

Model selection. We monitor the layer-wise neuron behaviors of a third-party DNN-based SR system, since generative adversarial networks (GANs) for voice synthesis are infeasible. Speaker recognition systems aim at determining the identity of speakers by learning the acoustic features mostly with DNN-based models. In this work, we exploit the DNN-based SR system to serve as a third-party model for capturing the layer-wise neuron behaviors by leveraging its power in representing speech in a layer-wise manner.

Layer selection. We select the layers which learn and preserve valuable representation information of inputs, such as convolutional and fully-connected layers in typical convolutional neuronal networks (CNNs). Other layers like pooling without learning substantial representation information are redundant layers in our work. It might be interesting to explore layers that specifically learn the differences between real and fake voices in future work.

Neuron coverage criteria. We introduce two different neuron coverage criteria to figure out the threshold $\delta$ for determining activated neurons. Then, the determined activated neurons in each selected layer are applied to represent the layer-wise behaviors of voices. Previous work [40] uses a global threshold to determine the neuron is activated or not, which is too coarse [23]. Here, we specify each layer a particular threshold. More details on calculating the threshold $\delta$ are presented in the following subsection.

3.4 Neuron Coverage Criteria Designing

In this paper, we introduce two different neuron coverage criteria for determining activated neurons to capture layer-wise neuron behaviors. The first one counts the number of activated neurons in each layer, called average count neuron (ACN). The other one selects neurons having top $k$ values in each layer, named Top-$k$ activated neuron (TKAN).

ACN. Motivated by the weakness of the global threshold defined in previous DNN testing studies, we specify each layer $l$ with a particular threshold $\delta_l$ which is calculated from the training dataset. The threshold $\delta_l$ is an average value of all the neuron output value in the layer $l$ of all inputs in the training dataset. We calculate the threshold $\delta_l$ with the following formula:

$$\delta_l = \frac{\sum_{x \in X, i \in I} \varphi(x, i; \theta)}{|I| \cdot |X|}$$

where $x$ is the neuron in $l$th layer, $X$ is the set of neurons in layer $l$, $i$ is the input in the training dataset $I$, $\varphi$ is the activation function for calculating the neuron output value of input $i$ with trained parameter $\theta$, $|X|$ and $|I|$ represent the number of neurons in layer $l$ and the number of inputs in training dataset $I$, respectively. Here,
we define the ACN as follows:

\[ \text{ACN}(l, i) = |\{ x | \forall x \in I, \phi(x, i; \theta) > \delta_l \}| \] (2)

where \( i \) represents the input, \( x \) is the neuron in layer \( l \), \( \phi \) is an activation function for computing the neuron output value, and \( \delta_l \) is the threshold of the \( l \)-th layer calculated by formula (1).

TKAN. Instead of learning a threshold from training datasets to determine whether a neuron is activated or not, we explore another neuron coverage criterion by simply selecting neurons whose output value is ranked as top \( k \) in its layer. Here, we conjecture that neurons with large output values are critical neurons which have high influences in representing inputs for a DNN model. We define the TKAN as follows:

\[ \text{TKAN}(l, i) = \{ \text{arg max}_k(\phi(x, i; \theta)) : x \in X \} \] (3)

where the function \( \text{arg max}_k \) returns \( k \) neuron output value calculated with \( \phi \). Here, the \( k \) is applied for all the layers in the model.

Figure 3 adopts t-distributed stochastic neighbor embedding (T-SNE), an algorithm for high-dimensional data visualization, to visualize the effectiveness of neuron behaviors in hunting the differences between real and fake voices compared with Mel-scale frequency cepstral coefficients (MFCC), a popular feature in speech analysis. From L-R, voices are represented with MFCC, raw layer-wise neuron behaviors, and activated neuron behaviors with designed neuron coverage criteria, respectively. We can easily find that compared with MFCC, raw layer-wise neurons can capture the differences between real and fake voices in a coarse manner, where the voices are separated into several relatively independent clusters. Furthermore, the subtle differences between real and fake voices can be easily distinguished by applying our designed neuron coverage criteria, where real and fake are separated into two independent clusters.

3.5 Fake Voices Detection

We train binary-classifier with a shallow neural network to predict whether a clip of voice is human speech or AI-synthesized fake voice. The inputs of our binary-classifier are the vectorized captured layer-wise neuron behaviors rather than the raw input of voices, which is better for a simple classifier to learn the differences between real and fake voices. Additionally, the neuron behavior inputs are insensitive to manipulations on voices, thus they are robust against various manipulations, such as voice conversion and additive real-world noises.

Algorithm 1: Algorithm for discerning fake voices with two different layer-wise neuron behaviors.

```
Input: Training and testing dataset of fake and real voices \( T \) and \( D \), DNN-based SR model \( \hat{M} \), top value \( k \)
Output: Label flag
1. Select layers from \( \hat{M} \) to monitor neuron behaviors.
2. \( L \leftarrow \text{LayerSelection}(\hat{M}) \)
3. Capture layer-wise neuron behaviors with ACN.
4. \( X_I \) is a set of neurons in layer \( l \) of \( \hat{M} \).
5. \( V_I \) counts activated neurons in layer \( l \) of \( \hat{M} \).
6. for \( i \in I \) do
7. \( S_I = \sum_{x \in X} \phi(x, i; \theta) \)
8. \( \delta_I = \frac{1}{|I|} \cdot S_I \)
9. for \( l \in L, i \in I, x \in X \) do
10. if \( \phi(x, i; \theta) > \delta_I \) then
11. \( V_I = V_I + 1 \)
12. Capture layer-wise neuron behaviors with TKAN.
13. \( N_I \) saves activated neuron output value in layer \( l \) of \( \hat{M} \).
14. for \( i \in I \) do
15. \( N_I = \text{arg max}_k(\phi(x, i; \theta)) \)
16. Train two independent binary-classifiers \( \tilde{C}_{acn}, \tilde{C}_{tkan} \) for ACN and TKAN with input vector \( V \) and \( N \) to discern fake voices.
17. \( \tilde{C}_{acn} \leftarrow \text{ClassifierTraining}(V) \)
18. \( \tilde{C}_{tkan} \leftarrow \text{ClassifierTraining}(N) \)
19. Predict whether a clip of voice in \( D \) is real or fake.
20. for \( d \in D \) do
21. \( \text{flag} \leftarrow \text{argmax} \tilde{C}_{acn}(d), \tilde{C}_{tkan}(d) \)
22. return flag
```

Algorithm 1 describes our basic ideas for capturing layer-wise neurons behaviors for discerning real and fake voices. We train two supervised binary-classifiers with the same architecture based on the two different strategies, namely ACN and TKAN. In predicting an input, we first obtain the layer-wise neuron behaviors with ACN and TKAN, respectively. Then, the neuron behaviors are formed as input features into the binary-classifier for prediction. For ACN, the number of activated neurons in each layer is formed as a feature vector. For TKAN, the raw value neuron output which ranked top \( k \) in its layer is formed as a feature vector. Finally, the classifier predict the voice based on the classifier’s final output score.

4 EXPERIMENTAL SETTING AND IMPLEMENTATION

In this section, we introduce the basic experimental settings, including datasets adopted for evaluation, baseline for comparison with prior work, and evaluation metrics. Additionally, we also present the implementation details.

4.1 Dataset

In our experiments, fake voices are collected from three different datasets including TTS and VC synthesized with various techniques. To ensure its diversity in languages and genders, English and mandarin Chinese languages are spoken by males and females.
with different accents are contained. The first dataset is a public dataset, called FoR, created by APTLY lab [37] with the latest open-sourced tools and commercial speech synthesis products (e.g., Amazon AWS Polly, Google Cloud TTS, and Microsoft Azure TTS). The real voices in FoR are collected from open-sourced speech datasets and free available videos on internet like TED talks and YouTube videos, which covers a good variety of genders, speaker ages, and accents, etc. All the fake voices are synthesized with latest deep learning-based techniques, which own high qualities. Unlike the public dataset released by Google [47] which adopts some outdated techniques for voice synthesis rather than state-of-the-art (SOTA) commercial products trained with massive powerful GPU resources. However, the dataset FoR only contains the first type TTS fake voices which are synthesized by given texts.

Therefore, we build the second dataset, a VC fake voice dataset. The dataset is built by ourselves with an open-sourced tool sprocket [16] which allows us to clone the source speaker’s identity into the target speaker. Sprocket also served as a baseline system in voice conversion challenge 2018 (VCC18) [21]. Here, real voices are collected from voice conversion challenge 2016 (VCC16) [46] and VCC18. The second dataset is called Sprocket-VC.

However, fake voices in the first and second datasets are all spoken in English language, thus we build the third dataset where fake voices are all spoken in mandarin Chinese for evaluating the capabilities of our approach in tackling different languages. We adopt the Baidu speech synthesis system [6] which achieves the best performance in Chinese language synthesis. We give a series of ancient poetry [32] as input texts to produce numerous fake voices. The third dataset is called MC-TTS. More details of the three datasets are shown in Table 1. We also present the length distribution of voices in the three datasets in Figure 4.

### 4.3 Evaluation Metrics
To get a comprehensive evaluation of DeepSonar, we adopt seven different metrics to evaluate the capabilities of DeepSonar in fighting against TTS and VC in the three datasets.

Specifically, we use accuracy, AUC (area under curve) of ROC (receiver operating characteristics), F1-score, and AP (average precision) to evaluate whether DeepSonar achieves a higher detection rate. We use FPR (false positive rate), FNR (false negative rate), and EER (equal error rate) to get the false alarm rate of DeepSonar in prediction. These seven metrics are widely served as metrics in evaluating the performance of classifiers.

### 4.4 Implementation Details
We design a shallow neural network with merely five fully-connected layers as our binary-classifier for discerning fakes. The optimizer is SGD with momentum 0.9 and the starting learning rate is 0.0001, with a decay of 1e-6. The loss function is binary cross-entropy.

In monitoring neuron behaviors, we employ a speaker recognition deep network that adopts a 'thin-ResNet' as its backend architecture [52] and select the convolutional and fully-connected layers to capture the layer-wise neuron behaviors as input features. Our approach is generic to any speech representation system, which could be easily extended to other systems that have the capability to learn speech representations layer-by-layer. For TKAN, we empirically set k to 5 with a consideration of the number of selected layers and training samples.

In evaluating the robustness of DeepSonar against manipulation attacks, we select more than 15 different manipulations to get a comprehensive evaluation. We hope that these 15 different representative voice manipulations could be served as a robustness evaluation benchmark for future research. Table 2 shows us the 15 different manipulations which are classified as voice conversions by changing voice signals and real-world noises by adding environmental noises. The real-world noise samples are collected from a public dataset ESC-50 that includes lots of environmental audio recordings [41].

All our experiments are conducted on a server running Ubuntu 16.04 system on a total of 40 cores 2.20GHz Xeon CPUs with 500GB RAM and four NVIDIA Tesla V100 GPUs with 36GB memory for each.
Table 2: Voice conversions and additive real-world noises in manipulation attacks. Voice conversion includes three common transformations when publishing audios. Additive real-world noises are classified into indoor and outdoor environmental sounds. The selected 12 real-world noises from ESC-50 are representative environmental sounds in real scenarios.

| Manipulation Attacks | Sound Classes |
|----------------------|---------------|
| Voice Conversions    | 1) resampling, 2) speed, 3) pitch |
| Real-world Noises    | Indoors 1) breathing, 2) footsteps, 3) laughing 4) mature-talk, 5) keyboard type, 6) clock-tick 7) engine, 8) train, 9) fireworks 10) rain, 11) wind, 12) thunderstorm  |
|                      | Outdoors 1) breathing, 2) footsteps, 3) laughing 4) mature-talk, 5) keyboard type, 6) clock-tick 7) engine, 8) train, 9) fireworks 10) rain, 11) wind, 12) thunderstorm  |

5 EXPERIMENTAL RESULTS

In this section, we conduct experiments in three datasets to comprehensively evaluate the effectiveness of DeepSonar in discerning AI-synthesized fake voices and its robustness against two typical manipulation attacks, voice conversions and additive real-world noises. Thus, our evaluation aims to answer the following two research questions.

- **RQ1**: What is the performance of DeepSonar in discerning two types of fake voices (TTS and VC) synthesized with various techniques and tackling different languages?
- **RQ2**: Whether DeepSonar is robust against voice manipulation attacks including voice conversions and additive real-world noises at various magnitudes?

5.1 Detection Results (RQ1)

In this section, we mainly answer the first research question, whether our approach DeepSonar can effectively discern real and fake voices and tackle different languages. Our experiments are conducted in the three different datasets in Table 1. Each dataset is divided into three parts, e.g., 60%, 20%, 20% as training, validation and testing, respectively. Specifically, we also compared our work with prior work using bispectral artifacts served as a baseline and report the detection rate and false alarm rate using seven different metrics.

**Effectiveness of DeepSonar.** Table 3 shows us the experimental results of DeepSonar using two different neuron coverage criteria for determining activated neurons. DeepSonar gives an average accuracy more than 98.1% and EER lower than 0.02 in the three datasets and demonstrates the effectiveness in discriminating the two typical fake voices in both English and Chinese languages. In the first dataset FoR where voices are synthesized with commercial products and more challenging than the other two datasets, DeepSonar gives an accuracy more than 99% when employing TKAN, but it reaches an accuracy less than 90% when adopting ACN. This result illustrates that using TKAN is more powerful than ACN in tackling voices synthesized with various commercial-level synthetic techniques. Thus, we mainly compare our approach using TKAN with baseline.

**Compared with baseline.** Table 4 gives the compared results with the baseline. Both the baseline and our proposed DeepSonar are trained and tested on the same datasets. Experimental results show that the average performance of DeepSonar using TKAN significantly outperforms the baseline in the three datasets. The baseline is a SOTA work using bispectral artifacts in fake voices to differentiate real and fake voices [1]. They found that higher-order spectral correlations rarely exist in real human speech while they are common in AI-synthesized fake voices. In their experiments, a simple classifier with SVM is adopted to identify the bispectral artifacts for differentiating real and fake voices. Different from this work investigating the artifacts introduced in synthesis, we leverage the power of layer-wise neuron behaviors for representing inputs, which provides cleaner signals than raw voice inputs (e.g., bispectral artifacts in voices) to simple binary-classifier in hunting the differences between real and fake voices.

According to the experimental results in Table 3 and Table 4, detecting clean AI-synthesized fake voices is a relatively easy task for our proposed approach DeepSonar. Unfortunately, voice manipulations like voices resampling, adding real-world noises are common in real applications, thus evading manipulation attacks is important for detectors deployed in the wild. In the next subsection, we mainly discuss the robustness of our approach in tackling manipulation attacks at various magnitudes.

5.2 Evaluation on Robustness (RQ2)

The biggest difference between AI-synthesized fake images and fake voices lies in that manipulations like voice conversion and additive real-world noises can be easily camouflaged as regular operations. In this section, we mainly evaluate the robustness of DeepSonar in tackling voice conversion and additive real-world noises at various magnitudes to answer the second research question.

**Experimental settings.** In experiments, we select 1,000 samples including 500 real and 500 fake voices from the testing dataset in FoR since they are synthesized with commercial products and...
The original clip of synthesized fake voice is from the FoR dataset saying “Do you feel like eating something”.

More challenging for detection. We also employ TKAN for DeepSonar and compare it with the baseline in terms of performance. AUC is adopted for evaluation metrics as it is often used in the binary-classifier performance evaluation. Additionally, we use signal to noise ratio (SNR) as metrics to evaluate the magnitude of real-world noises. The SNR is defined as follows.

\[
SNR = 20 \log \left( \frac{RMS^2_{signal}}{RMS^2_{noise}} \right)
\]

where \(\log\) is the logarithm of 10 and root mean square (RMS) is the root mean square.

By adding noises to voice data, we first need to obtain the RMS of the noises and voices, respectively. Then, we modify the noise by multiplying each element with a constant to change the RMS, thus desired SNR is given. In voice conversion, various voice manipulations are implemented with the APIs provided by lsbsora [34]. Figure 5 presents a spectral centroid visualization of the two manipulation attacks, the left is voice conversion and the right is additive real-world noises. The two manipulations all have obvious modifications to the signals, which poses challenges to detectors.

**Results on voice conversions.** Figure 6(a) presents us the experimental results of DeepSonar in tackling three typical voice conversions. Experimental results show that DeepSonar is robust against resampling including upsampling and downsampling without any performance affected. The average performance is decreased less than 5% and 15% in stretching the voices and shifting pitches, respectively. Compared to the other two conversions (resampling and speed), DeepSonar is a little susceptible to pitch shifting. The main reason is that voices with pitch shifting have been broken and can hardly listen to the words in voices when the \(n\_steps\) for changing the pitch of voices is larger than 2. The settings for the three voice conversions are presented as follows.

In voice conversion, resampling indicates a time series of voice which is resampled from the original sample rate to the target sample rate, including upsampling and downsampling. Here, the target sample rate is set with an offset (e.g., −400, 200, 0, 200, 400) to the original sample rate, where offset 0 servers as a baseline without resampling. Speed represents time-stretch an audio series by a fixed rate. The fixed-rate is set to 0.5, 0.8, 1.0, 1.2, 1.4, where 1.0 serves as a baseline. Pitch means we shift the pitch of a waveform by \(n\_steps\) semitones. Here, the \(n\_step\) is set to −4, −2, 0, 2, 4, where \(n\_step\) 0 serves as a baseline that no pitch is shifted.

**Results on indoor-noises.** In additive real-world noises, voices are added with representative indoor and outdoor environmental noises. We use SNR to measure the magnitudes of added-noises. In Figure 6(b), DeepSonar performs well on the five indoor noises and the average performance decreased less than 10% at the total five different magnitudes. However, the average performance is decreased by nearly 20% at the five magnitudes when adding footstep noises. We listened to the added-footstep voices which have obviously mixed sizzle noises caused by the friction with floors. Figure 5 also visualizes the differences between original voices and added-footsteps voices.

**Results on outdoor-noises.** In Figure 6(c), outdoor environmental noises can be classified into three different categories based on the performance of DeepSonar. Engine and thunderstorm environmental noises are the first categories, where the average performance of DeepSonar decreased less than 7% at the five different magnitudes. Fireworks and train are the second categories, where the average performance of DeepSonar decreased less than 18% at the five different magnitudes. Wind and rain are the third categories, where the average performance of DeepSonar decreased by nearly 25% at the five different magnitudes. We find that environmental noises wind and rain also mixed with other voices like rain drops on the ground which is noisier than other types of real-world noises.

According to the experimental results in Figure 6, DeepSonar is also robust against voice conversions except voices are seriously damaged like shifting pitch with a big step. Additionally, DeepSonar performs well when the additive real-world noises are single voice without any mixture with other types of noises. In tackling mixed noises like wind, DeepSonar also holds a high detection performance at the magnitude measured by SNR larger than 35.

**Compared with baseline.** The dotted lines in the three subfigures of Figure 6 show the comparison results with the baseline by using bispectral artifacts to discern fake voices. To compare the performance of robustness with baseline, we use the average results of the two approaches over different types of voice manipulations at various magnitudes. For example, in Figure 6(b), each point in the dotted line is an average AUC score of the six additive indoor noises at the same magnitude. In Figure 6, the dotted line of DeepSonar is above the baseline, which indicates that DeepSonar significantly outperforms the baseline in all the two manipulation attacks.

5.3 Discussion

Our proposed DeepSonar achieves competitive results on both effectiveness and robustness against two manipulation attacks. However, DeepSonar also has some limitations. Firstly, in adversarial environments, adversaries could add an additional loss function by modeling the neuron behaviors to generate adversarial voices and evade detection. However, almost all the learning-based approaches suffer this adversarial noise attack and an obvious trade-off between generating adversarial voices and evading detection has existed. Secondly, real-world noises with a mixture of other types of noises at a high magnitude could decrease the performance of DeepSonar to some extent. Voice denoising will be a potential strategy for high-intensity mixed noises, which could be our future work to remove...
additional environmental noises. Especially, the voice denoising component is effective without obtaining any prior knowledge of the noises in the complex environments.

6 CONCLUSIONS

In this paper, we proposed a novel approach, named DeepSonar, by monitoring neuron behaviors instead of investigating various artifacts introduced in voice synthesis to discern AI-synthesized fake voices with a simple binary-classifier. Experiments in the three datasets illustrate the effectiveness of our approach and evaluation on the two manipulation attacks demonstrates its robustness in tackling different voice conversions and additive real-world noises, which shows the potentials to be deployed in the wild. Furthermore, our work presents a new insight for detecting AI aided multimedia fakes by monitoring neuron behaviors, which aims to build an effective and robust detector.

In fighting against AI-synthesized voices, robustness should be considered as a priority in designing a detector, since various manipulations on voices can be easily camouflaged as regular operations, while manipulation on images is limited and easy to be spotted. Furthermore, the inconsistency of audio and visual in video DeepFakes is an important clue for DeepFake forensics, thus how to combine recent advances in fake still image and fake voice detection to spot the inconsistency is an important topic for future research. Our neuron behaviors based technique may be a promising idea. Producing and fighting fakes in the AI era is like a mouse and cat game. More powerful weapons should be continuously developed for fighting AI aided fakes as new techniques for producing various fakes will emerge inadvertently.

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