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WavLM and Omni-Scale CNNs: Enhancing Boundary Detection in Partially Spoofed Audio

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Abstract—**Partially spoofed/fake audio, in which segments of utterances are replaced with synthetic or natural audio clips, has emerged as a new form of deep audio forgery, posing potential severe threats to societal security. To address this issue, we employ a deep learning-based frame-level detection system, introducing a frame-level detection approach.We investigate the performance of WavLM in detecting waveform boundaries, utilizing WavLM as a feature extractor for original audio samples. Acoustic features and frame-level embeddings are concatenated, with an OS block embedded within the frame-level feature extraction process, in conjunction with CNN-1D to form the ResNet-OS network. This system can detect partially deceived audio and pinpoint the manipulated segments, effectively integrating multi-scale convolution to consider the interplay between local and global information in time series classification tasks. Experimental results show that this approach offers substantial generalization capabilities and robustness compared to traditional frame-level detection techniques.**

I. Introduction

Deepfake audio refers to sounds that are modified or created using deep learning technologies, aimed at deceiving both humans and machines. These technologies, particularly text-to-speech (TTS) and voice conversion (VC), have significantly enhanced the realism of synthetic voices, making them nearly indistinguishable from natural speech[1]–[3]. In this context, high-fidelity synthesis/conversion technologies invariably give thieves the tools they need to pose as someone else and conduct fraud. Therefore, the detection of audio forgeries is linked to societal security, privacy protection, and property safety, making it crucial to effectively detect deceptive speech to mitigate the potential threats posed by false information in audio content.

The ASVspoof Challenge is performed every two years to investigate defensive techniques against several kinds of spoofing attacks, such as synthetic speech, voice conversion, playback, and mimicry[4], in response to the concerns posed by audio spoofing assaults. However, many datasets and challenges have overlooked an important scenario. In this scenario, genuine speech is mixed with synthesized speech segments. This results in partial spoofing (PS).Attackers can use PS technology to modify key words in a sentence, such as time, place, and characters, thereby changing the semantic meaning of the sentence. This type of modification is low-cost and easy to perform. Therefore, defending against this PS scenario presents a significant challenge for defenders.

There have been notable developments in the field of Audio Deepfake Detection (ADD) with respect to PS scenarios in the last several years. Yi et al.[5]developed a dataset focused on altering several key words in semi-authentic audio, while Zhang et al.[6]designed the "PartialSpoof" voice database specifically for PS scenarios. These databases signify the commencement of PS scenario research within ADD tasks. Researchers have explored large-scale self-supervised pre-training models[7], [8],which have shown superior performance over traditional acoustic features such as MFCC and LFCC. Wu et al.[9] have developed a boundary detection system named "Fake Span Discovery", which is capable of identifying splicing boundaries. Additionally, Track 2 of ADD 2023 emphasizes the importance of accurately locating altered areas, making the research into the precise localization of spliced segments a more challenging and critical task. The performance of the boundary detection system still requires further enhancement.

This paper introduces a novel frame-level boundary detection system designed to identify partially spoofed audio. Unlike previous approaches that focused on utterance-level detection, our system exploits discontinuities between audio segments to accurately detect connection boundaries at the frame level. We employ WavLM as a feature extractor, together with the ResNet-OS architecture and a Transformer-based frame-level classifier for border identification. The HAD dataset was used to train the model, which was then evaluated on test sets. The results show that our system exceeds the performance of current partial fake audio detection methods in boundary detection.It achieved an Equal Error Rate (EER) of 0.06% on the HAD validation set and 0.023% on the HAD test set, demonstrating its cutting-edge ability to detect fabricated sections in audio streams.

II. Method

In this study, we focus on audio signals containing forged segments, with the objective to identify frames that contain discontinuous information. Given the acoustic feature input $X = (x_1, x_2, \dots, x_T) \in \mathbb{R}^{D\times T}$, where D represents the dimension of features and T represents the number of frames, this task is defined as a frame-level binary classification problem. The classification labels $y = (y_{1,}y_{2,\dots,}y_{T,}) \in \{0,1\}^T$.

Our system is capable of identifying specific frames that contain discontinuities. If a frame is located at the boundary

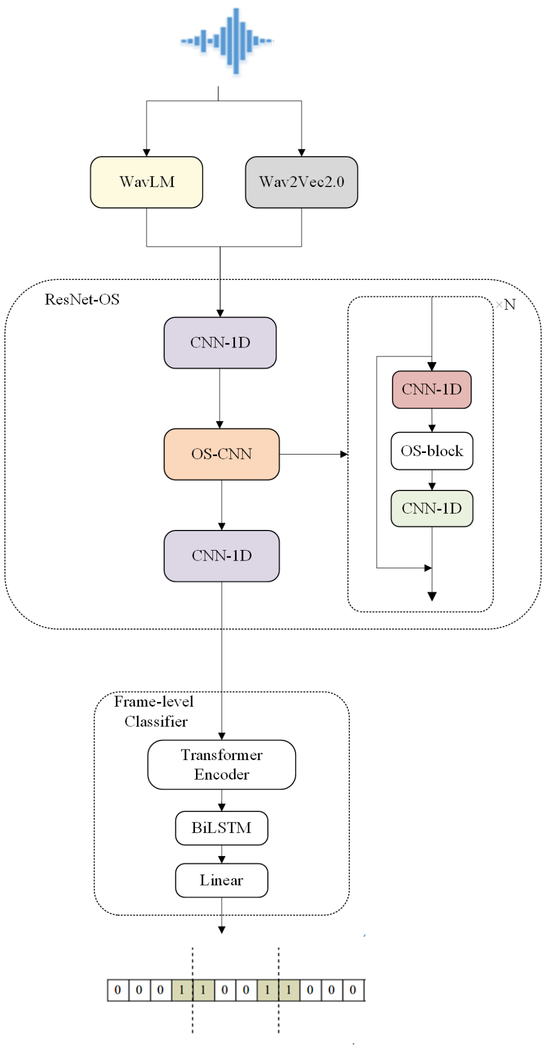

Fig. 1. The architecture of our proposed model

between forged and authentic audio, it is labeled as 1; otherwise, it is labeled as 0. To enhance the robustness of the system, frames close to the boundary are also marked as 1. This approach not only detects forged segments within the audio signal but also accurately pinpoints their locations.

A. Proposed Model

Figure 1 shows the design of our proposed model. We leverage the pretrained WavLM model[10] for feature extraction from the original audio. Subsequently, we utilize ResNet-OS to further extract frame-level embeddings. The combined Audio features and frame-level embeddings are sent into a Transformer-based classifier, which calculates the likelihood that each frame is a boundary.

B. Feature extraction

Wav2Vec[11]and WavLM[10]are two state-of-the-art self-supervised learning models that are primarily used for processing speech data. They have demonstrated exceptional performance in numerous downstream tasks, including automatic speech recognition (ASR)[12]. Consequently, we also employ these unsupervised models as feature extractors for original audio samples. We set the frame count T for both Wav2Vec and WavLM at 64, with an output feature frame rate of 20 milliseconds, culminating in a total feature dimension of 768.

C. Frame-level embedding extraction

After the feature extractor, we employ the ResNet-OS network to obtain frame-level embeddings, as illustrated in Figure 1. The ResNet-OS architecture includes two CNN-1D layers with N residual blocks sandwiched between them. Each residual block consists of two CNN-1D layers and an OS block, and features a residual connection that runs from the input to the output.

ResNet-OS is the core architecture of the model, consisting of N residual blocks, each configured as an OS-CNN. OS-CNN (Omni-Scale Convolutional Neural Network) is an architecture specifically designed for time series classification, based on the traditional 1D-CNN. This architecture incorporates OS block[13], enabling the model to effectively learn and extract features across various scales. Consequently, it excels in handling time series data characterized by complex patterns and dynamic changes. ResNet-OS includes two CNN-1D layers, between which N OS-CNN blocks are interspersed. Each OS-CNN block comprises two CNN-1D layers, with an OS block embedded between them. Moreover, the structure features a residual connection running from the input to the output to enhance learning capabilities and efficiency in information transfer. The architecture of the OS block, depicted in Figure 2, is a three-layer, multi-core convolutional network structure, where each convolutional layer employs multiple kernels and performs same-padding convolution operations. For configuring the kernel sizes, we use $p^{(i)}$ to represent the set of kernel sizes for the i-th layer:

$$P^{(i)} = \begin{cases} \{1,2,3,5,\ldots,p^k\} & i \in \{1,2\} \\ \{1,2\} & i = 3 \end{cases} \tag{1}$$

This set can include various sizes, allowing each layer to capture features at different scales. Typically, smaller kernels are capable of capturing more detailed features, while larger kernels can capture broader features.The core concept of the OS block (Omni-Scale Block) revolves around how to cover all possible receptive field (RF) sizes by selecting convolutional kernels of different sizes. The receptive field size, which means the size of the input region that generates the feature, has always been an important component influencing the performance of 1D-CNN in time series classification tasks.

The set of receptive field sizes, S, represents the collective receptive field sizes of all paths. This is the description of how the receptive field set S is calculated:

$$S = \left\{ p^{(1)} + p^{(2)} + p^{(3)} - 2 \mid p^{(i)} \in \mathbb{P}^{(i)} \right\} \tag{2}$$

Based on Goldbach's conjecture, which states that any even integer can be stated as the sum of two primes, allows us to broaden the receptive field set:

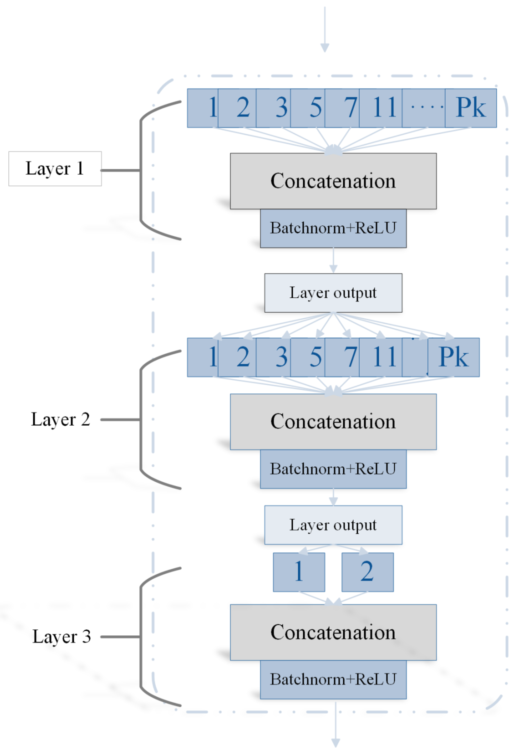

Fig. 2. Diagram of the OS block.

$$S = \left\{ e + p^{(3)} - 2 \mid p^{(3)} \in \mathbb{P}^{(3)}, e \in \mathbb{E} \right\} \tag{3}$$

where $\mathbb{E}$ is the set of all even receptive fields generated by the first two layers. Combining Equation (3) and Equation (1), we get:

$$S = \{e \mid e \in \mathbb{E}\} \cup \{e - 1 \mid e \in \mathbb{E}\} \equiv \mathbb{N}^{+} \tag{4}$$

$\mathbb{N}^{+}$ represents the set of all positive integers, indicating that through appropriate selection of convolutional kernels, it is possible to cover all receptive field (RF) sizes from 1 to the maximum possible size. Therefore, by properly choosing p^k, we can cover any range of integer receptive field sizes, thereby extracting more effective frame-level features.

D. Frame-level classifier

We use numerous Transformer encoders to record global context over vast distances across frames. We then further model the sequence embeddings produced by the Transformer encoders using BiLSTM. Ultimately, the boundary probability for every frame is estimated by a completely connected layer.

III. EXPERIMENT

A. Data Preparation

Our training data comes from the Half-truth Audio Detection (HAD) dataset[5]. This type of audio only modifies a few words in the original speech, posing a serious threat to audio verification systems, as these small-scale modifications are often difficult to detect. Table I provides statistics on the datasets used in our experiments. As shown in Table I,The HAD-train dataset consists of 26,554 real and 26,554 fake utterances, while the HAD-dev dataset contains 8,914 real and 8,914 fake utterances. All fake utterances in the HAD-train and HAD-dev datasets are generated using mainstream speech synthesis techniques. The HAD-test dataset includes 9,072 labeled utterances.

TABLE I
THE STATISTICS OF DATASETS (#UTTERANCES)

Name	Bona fide	Fake	ALL
HAD-train	26554	26554	53108
HAD-dev	8914	8914	17824
HAD-test	-	-	9072

The dataset for Half-truth Audio Detection (HAD) is derived from the AISHELL-3 corpus[14]. The Apache 2.0 license applies to this publicly accessible dataset. AISHELL-3 is a Mandarin voice corpus with many speakers that is utilized for text-to-speech (TTS) model training. We inserted audio segments into real speech according to the following strategy:

1. Named entity recognition and lexical annotation using jieba, followed by random replacement or substitution of these keywords with antonyms in order to change the semantics and emotional expression of the original utterance.

2. The (GST)-based Tacotron[15], [16] system is used to generate audio corresponding to the edited text, which is then processed by the neural vocoder LPCNet to enhance the naturalness and emotional expression of the synthesized audio and to ensure that its sound quality is consistent with the original recording.

3. The precisely processed synthesized audio is inserted into a specific position of the original audio, and the volume and sound quality are adjusted to ensure a seamless auditory integration and consistency between the synthesized part and the original audio.

As the final training data for the model, we merge some of the fake dataset with the actual discourse from the HAD-train dataset. Based on the HAD-test set, it is evaluated by combining it with the HAD-dev set as an adaptation dataset.

B. Parameter settings

ResNet-OS consists of 12 OS-CNN blocks, each containing a CNN-1D layer without bias, with a kernel size of 1 and both input and output sizes set to 512. The first CNN-1D operates without bias at a kernel size of 5, with an input size of 768 and an output size of 512. The final CNN-1D has a kernel size of 1, input size of 512, and outputs frame-level embeddings with an embedding size set to 128.

Four attention heads and two encoder layers make up the Transformer encoder of the frame-level classifier, which has a feed-forward network (FFN) size of 1024. The BiLSTM has 128 hidden units, and an activation function for ReLU comes after it. Lastly, each frame's probability is predicted using a 256-dimensional fully linked network.

C. Training Process

During the training process, genuine and fake utterances are considered identical since there is no boundary between them. We randomly select an audio sample from the partially fake dataset and a genuine sample from HAD-train, with a 0.5 probability of choosing a positive sample to maintain data balance. Each audio sample is trimmed to a fixed length,for instance, 0.64 seconds, 1.28 seconds, or 2.56 seconds. For online data augmentation, we leverage the MUSAN and RIR corpora. Positive samples' labels are set to all zeros. For negative samples, the label at the boundary between actual and fake audio clips is set to one, while the others are zero. Labels near the boundaries are likewise set to one.

In our experiments, the Adam optimizer and binary cross-entropy loss are used to train the model over 100 epochs. The learning rate is set at 10^{-4} and the batch size is set at 64. We assess the equal error rate (EER) on the test sets during training. For inference and assessment, we use the mean of the five models with the lowest EER for the wav2vec-based model. However, averaging models based on wavlm resulted in decreased performance. Therefore, for the wavlm-based model, we only consider the model with the best performance for evaluation.

IV. RESULTS AND DISCUSSION

Our research compared two systems: one trained with the Wav2Vec feature extractor and another with the WavLM feature extractor. The results are presented in Table II ,indicate that an audio length of 1.28 seconds offers the best performance for tasks using WavLM and Wav2Vec. This may be because this duration is sufficient to capture adequate contextual information without introducing noise or unnecessary details due to excessive length. Using Wav2Vec features, the model achieves an Equal Error Rate (EER) of 0.08% on the HAD-dev set and 0.067% on the HAD-test set at 1.28 seconds. For the WavLM model at the same duration, the EER on HAD-dev is 0.06%, and on HAD-test it is 0.023%, with performance degradation observed at audio lengths of 0.64 seconds and 2.56 seconds. These results suggest that the model trained with WavLM features exhibits superior generalization in this task compared to Wav2Vec.

TABLE II
SYSTEM PERFORMANCES REGARDING VARIOUS SEGMENT L, REPORTED IN EER.

Feature	Test Sets	Wav length l (s)		
		0.64s	1.28s	2.56s
Wav2Vec (w/o OS block)	HAD-dev	0.35%	**0.08%**	0.42%
	HAD-test	0.20%	**0.067%**	0.18%
WavLM	HAD-dev	0.19%	**0.06%**	0.28%
	HAD-test	0.12%	**0.023%**	0.10%

In this study, we adjusted the waveform length l to 1.28 seconds for models based on Wav2Vec and WavLM. We also conducted a series of ablation studies to analyze the performance impact of individual network components. As shown in Table III , We deleted specific components from the proposed network and documented their performance. Specifically, the"w/o ResNet-OS" model indicates the removal of the ResNet-OS component used for frame-level embedding extraction. For the Wav2Vec model, the equal error rate (EER) increased to 0.16% on the HAD-dev dataset and to 0.15% on the HAD-test dataset after removing ResNet-OS, demonstrating its critical role in model performance. Similarly, for the WavLM model, removing ResNet-OS resulted in an EER of 0.10% on HAD-dev and 0.05% on HAD-test. Removing the OS block lead to an EER of 0.073% on HAD-dev and 0.035% on HAD-test for the WavLM model, proving that the OS block also plays a significant role in enhancing model performance.

Overall, the WavLM model showed a better error rate performance compared to Wav2Vec, especially evident in the test set. These findings emphasize the critical role of the OS block and ResNet-OS structure in enhancing the accuracy of partial fake audio detection tasks, and removing these key components significantly reduces model performance.

TABLE III
PERFORMANCES (EER) REGARDING VARIOUS FEATURE EXTRACTOR AND ARCHITECTURE DESIGNS, W/O MEANS WITHOUT.

Model	HAD-dev	HAD-test
Wav2Vec	0.08%	0.067%
w/o ResNet-OS	0.16%	0.15%
WavLM	**0.06%**	**0.023%**
w/o ResNet-OS	0.10%	0.05%
w/o OS block	0.073%	0.035%

V. CONCLUSIONS

We designed a frame-level partial fake audio detection approach that not only delivers binary judgments at the utterance level for partially faked audio, but also accurately forecasts the insertion or replacement positions of false clips. By conducting ablation studies on our model components and evaluating various acoustic features, including Wav2Vec and WavLM, our experimental results demonstrate that this system outperforms existing boundary detection systems in detecting the boundaries of partially spoofed audio.

VI. ACKNOWLEDGEMENTS

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