ConvNext Based Neural Network for Anti-Spoofing

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Abstract. Automatic speaker verification (ASV) has been widely used in the real life for identity authentication. However, with the rapid development of speech conversion, speech synthesis algorithms and the improvement of the quality of recording devices, ASV systems are vulnerable to spoof attacks. In recent years, there have been many works about synthetic and replay speech detection, researchers had proposed a number of anti-spoofing methods based on hand-crafted features to improve the accuracy and robustness of synthetic and replay speech detection system. However, using hand-crafted features rather than raw waveform would lose certain information for anti-spoofing, which will reduce the detection performance of the system. Inspired by the promising performance of ConvNext in image classification tasks, we extend the ConvNext network architecture accordingly for spoof attacks detection task and propose an end-to-end anti-spoofing model. By integrating the extended architecture with the channel attention block, the proposed model can focus on the most informative sub-bands of speech representations to improve the anti-spoofing performance. Experiments show that our proposed best single system could achieve an equal error rate of 1.88% and 2.79% for the ASVSpoof 2019 LA evaluation dataset and PA evaluation dataset respectively, which demonstrate the model’s capacity for anti-spoofing.

Keywords: automatic speaker verification · anti-spoofing · end-to-end.

1 Introduction

Automatic speaker verification (ASV) systems use the speaker’s voiceprint information to identify characters, and has been widely used in many applications in real life. However, with the rapid development of the text to speech (TTS) algorithms \[1\], voice conversion (VC) algorithms \[3\], and the recording devices, the ASV systems are vulnerable to the spoof attacks.

In order to promote the research on spoof attack detection, the bi-annual anti-spoofing challenge was first held in 2015 \[5\]. Since then, many spoof attack detection methods had been proposed. And these works most focus on the feature engineering and network architecture designing. For the feature engineering,
hand-crafted features such as phase information [6], octave spectra information [7], Constant Q Cepstral Coefficients (CQCC) [8], CQT-based modified group delay feature [9] and genuinized feature that transformed from the given log power spectrum (LPS) [10] were proposed to enhance the effective of the anti-spoofing system. For the network architecture designing, the residual network and its variant [9,11] were used to detect the spoof attacks, Wu et al. [10] use a light convolutional neural network (LCNN) against spoofing attacks. Recently Li et al. [12] use a Res2Net architecture for replay and synthetic speech detection. Res2Net is a multiple feature scale network architecture. It split the features maps within one block into multiple channel groups and designs a residual-like connection across different channel groups, thus such design could increase the possible receptive fields and enhance the anti-spoofing capacity of the model. Although above residual network architecture or its variant achieve competitive performance for the spoof attacks detection, these single systems still lack of generalizability to unseen spoofing attacks. Ensemble systems that use different hand-crafted features would improve the anti-spoofing performance, but it will increase the model’s complexity.

Since extracting hand-crafted features would lose some useful information for detect the spoof attacks. For example, the phase information will be lost when the model applies Fast Fourier Transform (FFT) to extract features from raw waveform signal. Some researchers proposed the anti-spoofing model that directly use the raw waveform as the network’s input to capture the spoof cues of the spoof audio [13,14]. The results of these end-to-end systems are better than many anti-spoofing systems that use hand-crafted features.

Recently, Liu et al. modernized a standard ConvNet (ResNet [15]) towards the design of a hierarchical vision transformer and proposed a pure ConvNet model called ConvNext [16]. ConvNext had achieved great success in some vision tasks. Its classification performance demonstrated ConvNext’s powerful feature extraction capability. Inspired by the success of the residual network and its variant used for spoof attacks detection and the promising performance of the end-to-end spoof attacks detection, we design an end-to-end anti-spoofing neural network by extending the ConvNext’s network architecture. To the best of our knowledge, we are the first attempt to design an anti-spoofing neural network based on ConvNext network architecture. The major contributions of this paper are as follows:

- We proposed a new end-to-end anti-spoofing neural network (named CNBNN) based on the ConvNext’s network architecture, which achieved better or at least competitive performance with other anti-spoofing systems.
- We extend the original ECA layer of [17] and integrate it into the proposed end-to-end anti-spoofing neural network. Such a channel attention module could make the model focus on the most informative sub-bands of speech representations to improve the detection performance of the system.
- The proposed best single system could achieved an equal error rate (EER) of 1.88% and 2.79% on the evaluation dataset of ASVspoof 2019 LA and
PA corpus respectively, which demonstrate the anti-spoofing capacity of the model.

The rest of this paper is organized as follows: Section 2 illustrates the proposed ConvNext Based Neural Network and its integration with the modified ECA layer. Experiment setup, results and analysis are discussed in Section 3 and 4, respectively. We conclude this work in Section 5.

2 Proposed methods

This section will first present a general framework of our proposed system and then introduce the model’s resnet style block in detail. Finally, we will introduce the channel attention block that modified from the original ECA layer.

2.1 ConvNext based neural network architecture

As illustrated in figure 1(a), we adapt the ConvNext network architecture that from [16]. We revise the network to make it suitable for the input raw waveform, thus we can train the neural network end-to-end. Compared with the original network architecture, we remove the Stochastic Depth [18], which we find do not improve the performance of the anti-spoofing system. For the normalization method, we replace layer normalization with batch normalization and achieve a better performance for anti-spoofing. We assume that the network should be relatively shallower because deeper network extract deeper features which towards higher level semantic information, but it may not suitable to represent the subtle forgery artifacts from the spoof attacks. So we change the different compute stage ratio 3:3:9:3 to be 1:2:3:1 to make the network shallower. We use a maxpooling layer with a large kernel size of 7 to downsample the feature map instead of just use conv layer except the stem layer. And we set the channel of each compute stage to be (16,32,64,128). For the activation function, we replace GELU with SMU, which is a novel activation function using the smoothing maximum technique, it can outperform widely used activation functions in a variety of deep learning tasks [19]. For the ResNet style Block in the network, we integrate a channel attention module that modified from the ECA layer with it to enhance the model’s robustness and generalization capacity.

2.2 ResNet style block

As illustrated in figure 1(b), the ResNet style block use a reverted bottleneck. It means that the hidden dimension of the MLP block is four times wider than the input dimension. It is assume that compared with the bottleneck block that used in many network architecture before, it enlarge the channel information instead of compress it, thus it can enrich the number of features, so as to improve the accuracy. To be specify, the input feature maps were first through a depthwise conv layer to enlarge the channel dimension, and then a pointwise conv layer is used to fuse information between each channel. In the experiment, the pointwise conv layer is implement with linear layer.
2.3 modified ECA layer

To further enhance the robustness and generalizability of the model, we use a channel attention module that revise from the original ECA layer to make it suitable for the input raw waveform. ECA layer is a channel attention module that revise from the SE Block [20], it is assume that dimensionality reduction that used in SE block is unnecessary to capture the dependencies between each channel. So in ECA layer, it avoids dimensionality reduction and captures cross-channel interaction in an efficient way. As illustrated in figure 2, after channel-wise global average pooling (GAP) without dimensionality reduction, the modified ECA layer capture local cross-channel interaction by considering every channel and its k neighbors. Such a strategy can be efficiently implemented by fast 1D
convolution of size \( k \), where kernel size \( k \) represents how many neighbors participate in attention prediction of one channel. And in this work, we use the method that used in \[17\] to adaptively select the kernel size, which is proportional to channel dimension. Such a channel attention module could make the model learn to emphasize important features and suppress useless features. Thus the model could focus on the most informative sub-bands of speech representations and have a better performance for spoof attacks detection.

3 Experiment setup

In this section, we first present the dataset and evaluation metrics that we used in the experiment. Then, we introduce the details of system implementation.

3.1 Dataset and evaluation metrics

We use the logical access corpus and physical access corpus of ASVspoof2019 Challenge \[21\] to evaluate the performance of our proposed system. As illustrated in table \[1\] the LA and PA dataset are all partitioned into three parts for training, development and evaluation, and each part includes genuine speech and spoofed speech. For the PA dataset, there are 54000 samples for training, 29700 samples for development and 134730 samples for evaluation. For the LA dataset, there are 25380 samples for training, 24844 samples for development and 71237 samples for evaluation.

We use the equal error rate (EER) and the tandem detection cost function (t-DCF) as the primary metrics to evaluate the proposed anti-spoofing system. The t-DCF takes both the ASV system and spoofing countermeasure errors into consideration. For the ASV system, the lower the t-DCF, the better system performance. More details of t-DCF can be found in \[22\].
Table 1. Summary of the ASVspoof 2019 corpus

| Partition | Physical Access | Logical Access |
|-----------|-----------------|----------------|
|           | #Bonafide | #Spoofed | #Bonafide | #Spoofed |
| Train     | 5400      | 48600    | 2580      | 22800    |
| Dev.      | 5400      | 24300    | 2548      | 22296    |
| Eval.     | 18090     | 116640   | 7355      | 63882    |

3.2 Details of system implementation

In this study, we do not extract the hand-crafted features from the raw waveform. We directly use the raw waveform as the input of the proposed network to train the model end-to-end. Since the speech data of ASVspoof 2019 is recorded with varied durations, we have to align the speech data, all examples should be truncated or repeated until the duration is the same. And in the experiments, we keep all the speech data of LA dataset and PA dataset with 6 seconds.

We implement the algorithms in the PyTorch framework. We train each model with 50 and 100 epochs for LA and PA dataset, respectively. And the batch size is set to 32. The model with lowest EER on development set is chosen to be evaluated. We select AdamW [23] as the optimizer with the initial learning rate of 0.001. Exponential learning rate decay with a multiplicative factor of 0.95 is adopted. Considering the fact that the number of genuine examples is much less than the number of fake ones in ASVspoof 2019 LA and PA dataset, we apply weighted cross-entropy (WCE) loss during the training phase to cope with data imbalance. Finally, the anti-spoofing system’s output is directly adopted as the countermeasure (CM) score.

4 Results and analysis

4.1 Comparison with ASVspoof 2019 baseline

The proposed system is an end-to-end model that directly use the raw waveform as the network’s input, and a channel attention module is integrated into the system to further enhance the anti-spoofing performance of the system. The model without the channel attention module is the baseline system. Further, we also consider two baseline anti-spoofing systems of ASVspoof 2019 challenge. They are based on CQCC and LFCC features with Gaussian mixture model (GMM) classifier.

Table 2 and 3 show the results of the proposed CNBNN, its integrate with the channel attention module(mECA) on ASVspoof 2019 logical and physical corpus and their comparison to the baseline systems. For the LA test, we observe that the proposed channel attention module could improves the model’s anti-spoofing capacity. The improvement in the evaluation set that contains more spoof attacks of unseen nature is evident. Integrate the channel attention module decrease the EER from 3.00% to 1.88%. For the PA test, we observe that the model with
channel attention module could achieve slightly better performance on both the development set and evaluation set. The model with channel attention module could achieve an EER of 2.14% and 2.79% for the PA development set and evaluation set, respectively. The experiment results confirms our hypothesis that use the channel attention module could make the model focus on the most informative sub-bands of speech representations and thus have a better performance for anti-spoofing. Also, we find that the performance of the proposed system is much better than the two baselines of ASVspoof 2019 challenge.

**Table 2.** Performance of the proposed systems and their comparison to the baseline systems on ASVspoof 2019 logical access corpus.

| System            | Development set | Evaluation Set |
|-------------------|-----------------|----------------|
|                  | min-tDCF | EER(%) | min-tDCF | EER(%) |
| CQCC-GMM[24]     | 0.012   | 0.43   | 0.237  | 9.57   |
| LFCC-GMM[24]     | 0.063   | 2.71   | 0.212  | 8.09   |
| CNBNN             | 0.022   | 0.67   | 0.068  | 3.00   |
| CNBNN+mECA       | 0.012   | 0.47   | 0.051  | 1.88   |

**Table 3.** Performance of the proposed systems and their comparison to the baseline systems on ASVspoof 2019 physical access corpus.

| System            | Development set | Evaluation Set |
|-------------------|-----------------|----------------|
|                  | min-tDCF | EER(%) | min-tDCF | EER(%) |
| CQCC-GMM[24]     | 0.195   | 9.87   | 0.245  | 11.04  |
| LFCC-GMM[24]     | 0.255   | 11.96  | 0.302  | 13.54  |
| CNBNN             | 0.062   | 2.28   | 0.087  | 3.11   |
| CNBNN+mECA       | 0.056   | 2.14   | 0.073  | 2.79   |

### 4.2 Comparison with other single systems

In this section, we compare our best single system with some known single systems on the ASVSpoof 2019 PA and LA evaluation dataset, respectively. The results are shown in table 4 and table 5.

For the LA corpus, we observed that only a few systems could achieve an equal error rate (EER) below 2.5% on the LA evaluation set. Compared with other single systems that use hand-crafted features, such as CQCC, LFCC and CQT, our proposed best single system could achieve a better performance on detecting the spoof attacks. And for the anti-spoofing system that used Res2Net network architecture, our proposed best single system could outperform it with a large margin and have a relative EER reduction of 24.8%. For the single systems
which also use the raw waveform as the system’s input, i.e. RW-ResNet and RawNet2, our best single system also outperform them. For the PA corpus, we observed that our proposed best single system could also achieve a better performance than many but one single systems that use hand-crafted feature. The experiment results demonstrate the effectiveness and generalization ability of our proposed system.

**Table 4.** Performance of the proposed best single systems and its comparison to other single systems on ASVspoof 2019 logical access corpus.

| System                        | EER(%) | min-tDCF |
|-------------------------------|--------|----------|
| CQCC+ResNet [11]              | 7.69   | 0.217    |
| LFCC+LCNN [25]                | 5.06   | 0.100    |
| FFT+LCNN [25]                 | 4.53   | 0.103    |
| RawAudio+RawNet2 [14]         | 4.66   | 0.129    |
| FG-CQT+LCNN [10]              | 4.07   | 0.102    |
| DASC-CQT+LCNN [26]            | 3.13   | 0.094    |
| RawAudio+RW-Resnet [13]       | 2.98   | 0.082    |
| CQT+SERes2Net50 [12]          | 2.50   | 0.074    |
| Resnet18+OC-softmax [27]       | 2.19   | 0.059    |
| LFCC+Capsule network [28]     | 1.97   | 0.054    |
| LCNN-LSTM-sum [29]            | 1.92   | 0.052    |
| **Ours:CNNBNN+mECA**          | **1.88** | **0.051** |

**Table 5.** Performance of the proposed best single systems and its comparison to other single systems on ASVspoof 2019 physical access corpus.

| System                        | EER(%) | min-tDCF |
|-------------------------------|--------|----------|
| Siamese CNN+CQCC [30]         | 10.08  | 0.245    |
| Siamese CNN+LCNN [30]         | 7.98   | 0.195    |
| STFT log+CapsNetFC [31]       | 4.93   | 0.120    |
| LFCC+LCNN [25]                | 4.60   | 0.105    |
| CQCC+ResNet [11]              | 4.43   | 0.107    |
| Spec+ResNet [11]              | 4.07   | 0.102    |
| **STFT gram+Capsule network** [28] | **2.77** | **0.073** |
| **Ours:CNNBNN+mECA**          | 2.79   | 0.073    |

5 Conclusions

This work proposes a new end-to-end anti-spoofing system. We revise the ConvNext network architecture and then integrate a channel attention module that
modified from the original ECA layer with it to further enhance the model’s anti-spoofing performance. Experimental results shows that compared with other single systems, our proposed best single system could achieve a promising performance on LA and PA scenarios. In the future, we will apply the proposed system to other speech tasks.

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