Detection of Voice Transformation Spoofing Based on Dense Convolutional Network

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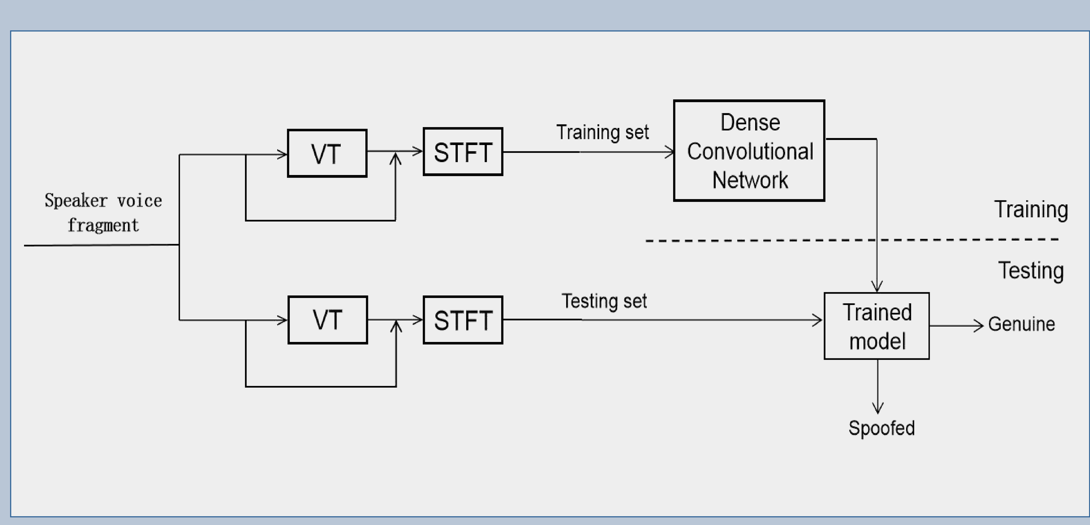
Abstract

- Nowadays, speech spoofing is so common that it presents a great challenge to social security. Thus, it is of great significance to recognize a spoofed speech from a genuine one.
- Most of the current researches have focused on voice conversion (VC), synthesis and recapture which mimic a target speaker to break through ASV systems by increased false acceptance rates. However, there exists another type of spoofing, voice transformation (VT), that transforms a speech signal without a target in order 'not to be recognized' by increased false reject rates. VT has received much less attention. Thus, in this paper, we investigate the model of VT and propose a method using a very deep dense convolutional network with 135 layers to detect VT spoofed speeches from genuine speeches. The experimental results show that the average accuracies over intra-database and cross-database outperform the reported state-of-the-art methods.

The Experimental Process



Acknowledgement

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Methods

- In a conventional CNN, the output of the previous layer $X_{\ell-1}$ is transmitted to the next layer as input by a non-linear operation H_ℓ to get the output X_ℓ.

$$X_\ell = H_\ell(X_{\ell-1}) \qquad (1)$$

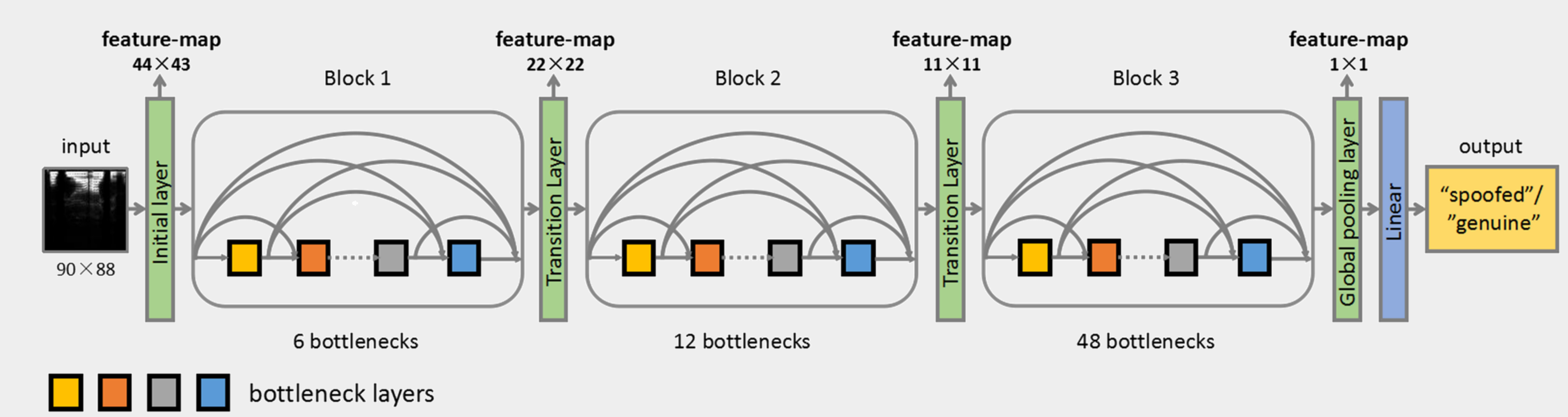
- It is difficult to train a conventional CNN as degradation occurs with the increment of layers. To have a good inhibitory effect on the degradation, Residual Networks (ResNets)[1], Highway Networks[2] and FractalNets[3] create short paths $X_{\ell-\alpha}$ from early layers to later layers as shown in Equ.(2).

$$X_\ell = H_\ell(X_{\ell-1}) + X_{\ell-\alpha} \qquad (2)$$

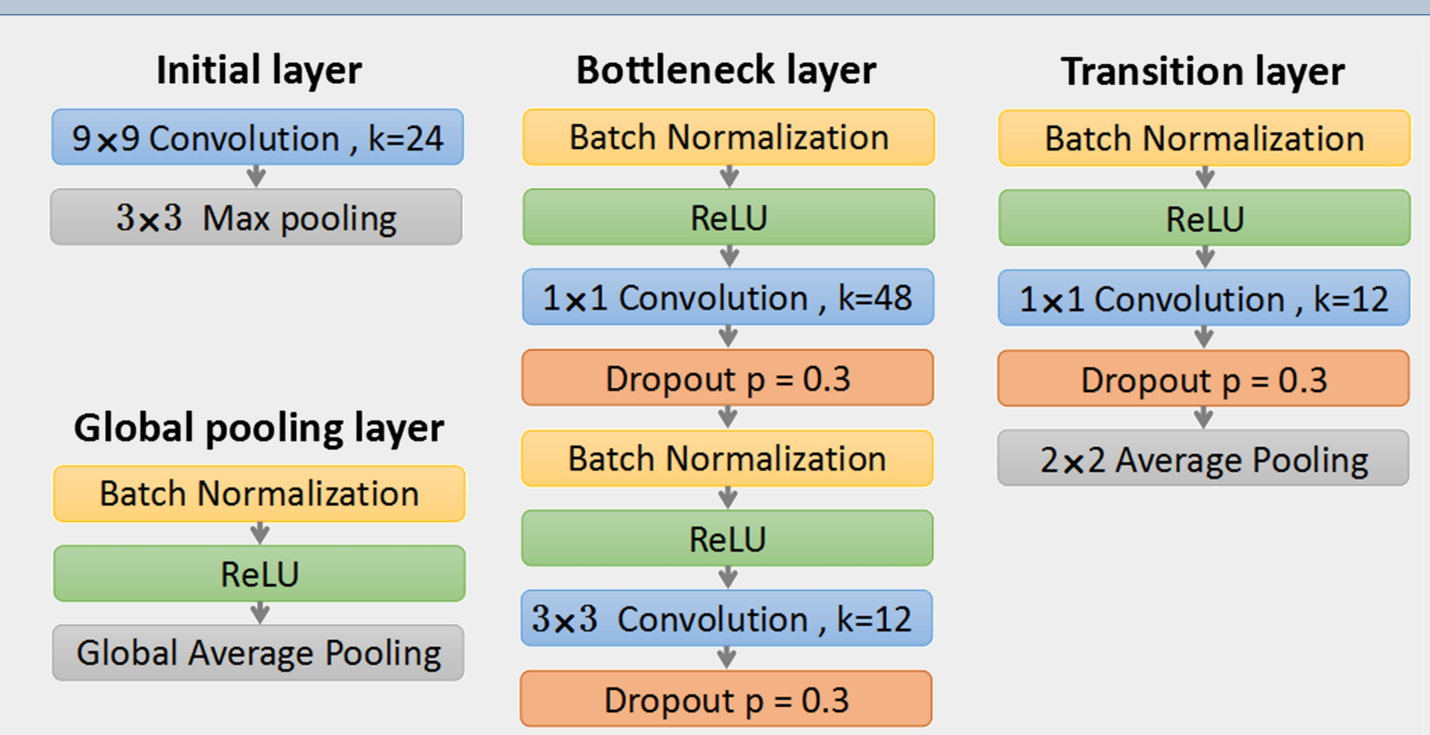
- However, recent research suggests that this type of connection leads to the fact that many layers contribute very little but occupy a large amount of computation [4]. Thus, an improved structure of ResNet named Dense Convolutional Network (DenseNet) was proposed to avoid this problem. In a DenseNet, any layer has direct connections to all subsequent layers, as shown in Equ.(3)

$$X_\ell = H_\ell([X_0, X_1, \ldots, X_{\ell-1}]) \qquad (3)$$

- where $X_0, X_1, X_{\ell-1}$ represent the output of the previous layer of layer ℓ and $[\ldots]$ on behalf of the concatenation operation. Furthermore, the output dimension of each layer has k feature maps, where k is usually set to a small value.



The architecture of the proposed network (135 layers)



- The inner structures of each kind of the layers. BatchNormalization, ReLU, Dropout and Pooling are ofthe operations before and after the convolution layer. k refers to the number of convolution kernels.

Results

a.The detection accuracy of intra-database evaluation

Training set	Testing set	Proposed Method	Liang's Method	Wu's Method
TIMIT_1	TIMIT_2	99.45%	96.52%	95.87%
NIST_1	NIST_2	98.04%	95.93%	94.56%
UME_1	UME_2	97.56%	94.85%	93.63%

b.The detection accuracy of cross-database evaluation

Case	Training set	Testing set	Proposed Method
Case1	TIMIT_1/NIST_1	UME_2	96.45%
Case2	NIST_1/UME_1	TIMIT_2	95.26%
Case3	TIMIT_1/UME_1	NIST_2	80.20%

Reference

- [1] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, "Deep residual learning for image recognition," pp. 770–778, 2015.
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Conclusion

- In this paper, a method based on dense convolutional network for detecting spoofed speech from genuine speech is presented. Deep features can be automatically extracted by the 135-layer DenseNet. It achieves computing efficiency by careful optimization of kernel reduction and by the employment of bottleneck layers. The experimental results indicates that it is superior to the state-of-the-art methods. The future work will focus on the extraction of deeper features to further improve the accuracy.

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