LIP-READING WITH HIERARCHICAL PYRAMIDAL CONVOLUTION AND SELF-ATTENTION

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ABSTRACT
In this paper, we propose a novel deep learning architecture to improve word-level lip-reading. On the one hand, we first introduce the multi-scale processing into the spatial feature extraction for lip-reading. Specially, we propose hierarchical pyramidal convolution (HPConv) to replace the standard convolution in original module, leading to improvements over the model’s ability to discover fine-grained lip movements. On the other hand, we merge information in all time steps of the sequence by utilizing self-attention, to make the model pay more attention to the relevant frames. These two advantages are combined together to further enhance the model’s classification power. Experiments on the Lip Reading in the Wild (LRW) dataset show that our proposed model has achieved 86.83% accuracy, yielding 1.53% absolute improvement over the current state-of-the-art. We also conducted extensive experiments to better understand the behavior of the proposed model.

Index Terms— Visual Speech Recognition, Lip-reading, Multi-scale Convolution, Self-attention

1. INTRODUCTION
Automatic lip-reading, also known as visual speech recognition, aims to recognize the speech content only based on visual information, especially the lip movements which are also named as visual speeches/sounds or visemes [1]. Lip-reading becomes a very challenging task for both human and machine, due to the ambiguity introduced by the one-to-many mapping [2] between viseme and phoneme. But a robust lip-reading system has a broad range of applications when the audio data is unavailable, such as silent speech control system [3], assisting audio-based speech recognition in noisy environments [4], biometric authentication [5].

Traditional approaches usually consist of a spatial feature extractor, such as discrete cosine transform [6] to the lip Regions of Interest (RoIs), and followed by a sequential model which is usually a hidden markov model [9] to capture the temporal dynamics. More details about these older approaches are in [12]. Recently, two developments have been significantly improving the automatic lip-reading: the use of deep neural network models [13] [14] [15], and the availability of a large scale dataset for training [16] [17] [18]. Most deep-learning-based models usually consist of a frontend module and a backend module, which are similar to the feature extractor and the sequential model in traditional approaches, respectively. However, using end-to-end training, the frontend module can extract more discriminative features than traditional extractor, and the backend module can capture more temporal information than the traditional approaches.

In this work, we focus on the word-level lip-reading and choose the Lip Reading in the Wild (LRW) [16] dataset as the benchmark. The current state-of-the-art (SOTA) performance on LRW is achieved by [15], which also is our baseline model. It consists of a 3D Convolutional layer followed by a 18-layer Residual Network (ResNet-18) [19] and a Multi-Scale Temporal Convolutional Networks (MS-TCN), which are applied as the frontend and the backend, respectively. The final feature map at the sequence level is obtained by averaging the output of the backend along the time dimension. The process of merging feature maps in all time steps is called "Consensus".

In this paper, we improve the performance of the current SOTA model. We revamp the frontend and the consensus to achieve a new SOTA. For the frontend, we proposed a novel hierarchical pyramidal convolution (HPConv) to replace the standard 2D-convolution in the ResNet-18, which is capable of processing the input with multiple spatial resolution. Moreover, our proposed model utilises the self-attention based consensus, which makes the frames related the annotated word play a greater role during classification. To the best of our knowledge, this is the first work introducing the multi-scale processing into the frontend and proposing changes in consensus for word-level lip-reading.
2. RELATED WORKS

LRW is the first and the largest publicly available dataset with word-level label in English. It consists of short segments (1.16 seconds) from BBC news and talk shows. There are more than 1000 speakers and 500 target words, which is much higher than existing lip-reading databases used for word recognition. A total of 538766 segments in this dataset are split into 488766/25000/25000 for training/validation/testing usages. This is a quite challenging dataset due to the large number of variations in head pose and illumination.

| Method           | Frontend          | Backend      | Consensus | Accuracy |
|------------------|-------------------|--------------|-----------|----------|
| VGG-M            | -                 | LSTM         | Average   | 61.10    |
| VGG-M            | -                 | BLSTM        | Average   | 76.20    |
| 3D Conv+ResNet-34| BLSTM             | Average      | 84.48     |
| 3D Conv+ResNet-34| BGRU              | Average      | 83.4      |
| 3D Conv+ResNet-18| BLSTM             | Average      | 84.3      |
| ResNet-34+       | Conv-BLSTM        | Average      | 83.5      |
| 3D DenseNet      | 13D+2             | Average      | 84.07     |
| P3D-ResNet-50    | BLSTM             | Average      | 84.48     |
| 3D Conv+ResNet-18| MS-TCN            | Average      | 85.30     |
| 3D Conv+ResNet-34| BGRU              | Average      | 84.25     |

Table 1. Review of the existing models on LRW

Since LRW is released, numerous novel models were proposed for more powerful word-recognising abilities. We give a brief review of the previous models on LRW with their respective frontend type, backend type, consensus method and top-1 accuracy (abbreviated as accacy in the following), shown in Table 1.

3. OUR APPROACH

As shown in Fig. 1 our model can be divided to three main parts: the frontend module, the backend module and the consensus module. The frontend takes a grayscale sequence of lip RoIs $X \in \mathbb{R}^{T \times H \times W}$ as input, where $T$ stands for the temporal dimension and $H, W$ represent the height and width of the grayscale of lip respectively, and produce the feature $F_2 \in \mathbb{R}^{T \times C_1}$, which the spatial knowledge is summarised by applying the average pooling over the spatial dimensionality. After the frontend, the backend module is employed to model the temporal dynamics. The output $F_3 \in \mathbb{R}^{T \times C_2}$ is passed through the the consensus module to merge temporal information. Finally, the posterior probability of each word class $P$ is predicted by the ensuing a full connection layer and a SoftMax layer.

We maintain the multi-scale TCN in the baseline as the backend but change the frontend and the consensus. In the frontend, we replace the standrad convolution in the ResNet-18 with the hierarchical pyramidal convolution. Besides, the average based consensus is replaced by the self-attention based consensus.

3.1. Hierarchical Pyramidal Convolution

![Fig. 2. Illustration of the PyConv. The illustration is adapted from [23]. Local and global feature maps are extracted from the input feature maps respectively. ⊛ denotes the convolution operation.](image_url)

![Fig. 3. Illustration of the Proposed HPConv. Local feature maps also used to extract global feature maps. ⊛ denote the concatenation over channel dimension.](image_url)

The ResNet-18 in the frontend of the baseline uses the standard 2D-convolution to extract spatial feature maps. The standard convolution contains a single type of kernel with a single spatial size $(K_1, K_1)$ (in the case of square kernels). All $C_o$ kernels have the same spatial resolution, which lead to
a constant receptive field.

We analyze the error samples of the baseline, and find that the accuracy of word recognition increases with the number of viseme contained in the word. In other words, the model does not well on words with pool visemic content. This is reasonable, because the fewer visemes mean the fewer lip movements, which adds many extra difficulties for the model to classify sample correctly. Based on this, we proposed that applying different spatial size of kernels during the feature extraction can bring complemented spatial context information, which enables the frontend can extract more distinct feature maps. These discriminative features help boosting the insight of the model into fine-grained lip movements and improve classification accuracy on words with few visemes.

To validate the effectiveness of the multi-scale processing, we first introduce pyramidal convolution (PyConv) [25] into the frontend. The PyConv, illustrated in Fig. 2 contains a pyramid with n levels of different types of kernels (We set n = 4 as default in our experiments, which is consistent with the figure). The kernels at each level contains an increasing spatial sizes from the bottom of the pyramid to the top (We set $K_{1,2,3,4} = 3, 5, 7, 9$ as default in our experiments). The kernels with smaller spatial size can focus on details to extract feature maps with local context information, while the larger kernels can provides more global context information. The model can explore a best combination of different kernel types through learning. For every basic block of the ResNet-18, we replace the second standard convolution layer to the PyConv. We call this moditication as the Pyramidal ResNet-18 (Py-ResNet-18).

Based on the PyConv, we propose hierarchical pyramidal convolution (HPConv), illustrated in Fig. 3. The most innovative point is that we establish a hierarchical connection between adjacent layers of the pyramid (Red lines in Fig. 3). As mentioned above, the local and global feature maps in the PyConv are extracted from the input feature maps respectively. And with the hierarchical connection, the local feature map is used as a part of the output, also an input for the global feature extraction. We proposed that this bottom-up information aggregation can further improve the classification performance of the model, especially on words with few visemes. For every basic block of the ResNet-18, we replace the second standard convolution layer to the HPConv. We call this modification as the Hierarchical Pyramidal ResNet18 (HP-ResNet-18).

### 3.2. Self-attention based consensus

The most popular consensus method currently is to average over all the time steps, as shown in Table 1. For the average based consensus, given the feature maps at the frame level $F_3 \in \mathbb{R}^{T \times C_2}$, the final feature at the sequence level $F_4 \in \mathbb{R}^{C_3}$ is calculated as follows:

$$F_4 = \frac{\sum_{t=0}^{T-1} F_{3,t}}{T} \quad (1)$$

The average based consensus assumes that every frame provides an equal contribution to the final decision, which is not the case in practice. As shown in Fig. 4 the video sample annotated as "ABOUT" includes 29 frames in total, but only frames at time step $T = 9 \sim 19$ are related with the word "ABOUT". The average based consensus method assumes that every frame has equal contribution to the final decision, which is not the case in practice. As shown in Fig. 4 the video sample annotated as "ABOUT" includes 29 frames in total, but only frames at time step $T = 9 \sim 19$ are related with the word "ABOUT". Based on this, we propose a self-attention based consensus method to ensure the model pay more attention to the frames which are related with annotated word, but less to other irrelevant frames. Our self-attention based consensus can be expressed as:

$$Q_n, K_n, V_n = F_3 W^Q_n, F_3 W^K_n, F_3 W^V_n \quad (2)$$

$$H_n = A_n^T V_n = \text{SoftMax} \left( \frac{\sum_{t=0}^{T-1} Q_{n,t} K_{n,t}}{T \sqrt{d_k}} \right) V_n \quad (3)$$

$$F_4 = W^O \text{Concat}(H_0, \cdots, H_{N-1}) + \frac{\sum_{t=0}^{T-1} F_{3,t}}{T} \quad (4)$$

where the projection matrices $W^Q_n \in \mathbb{R}^{C_2 \times d_k}$, $W^K_n \in \mathbb{R}^{C_2 \times d_k}$, $W^V_n \in \mathbb{R}^{C_2 \times d_v}$ and $W^O \in \mathbb{R}^{N d_c \times C_3}$, the attention weight $A_n \in \mathbb{R}^{T}$. In this work we employ $N = 8$ heads and $d_k = d_v = 64$, same with [26]. Even though each head has a different focus, the attention weight on all irrelevant frames should be 0, which helps the model to ignore noisy information for better classification performance.

### 4. EXPERIMENT RESULTS

| Model   | Frontend       | Consensus       | Boundary | Accuracy |
|---------|----------------|-----------------|----------|----------|
| baseline| ResNet-18      | Average         | F        | 85.3     |
| N1      | ResNet-18      | Self-attention  | F        | 86.47    |
| N2      | Py-ResNet-18   | Average         | F        | 85.88    |
| N3      | HP-ResNet-18   | Average         | F        | 86.45    |
| N4 (Our)| HP-ResNet-18   | Self-attention  | F        | **86.83**|
| N5      | ResNet-18      | Average         | T        | 88.60    |
| N6      | ResNet-18      | Self-attention  | T        | 88.59    |

Table 2. A comparison of the performance between the baseline and our models. Our model attain the state-of-the-art on LRW. 3D Conv in the frontend is omitted for simplicity.
In this section, we compare our model with the baseline model. And to understand the contribution of different parts of our model better, we also analyze the results of the ablation experiment. We pre-process each video process and train all models following the same method as the baseline. The readers are referred to [15] for more details.

Table 2 lists the results of all models. Compared to the baseline model, our proposed model (denoted by N4) achieves an absolute improvement of 1.53% in classification accuracy, which means our model attain the state-of-the-art by a wide margin on LRW.

4.1. Discussion about Proposed HPConv

To verify the effectiveness of our proposed HPConv on classification performance, we present the result of the model using only the HP-ResNet-18 in Table 2 (denoted by N3), along with the result of the model using only the Py-ResNet-18 (denoted by N2), as it constitutes the starting point for our work on the multi-scale process in lip-reading. Compared with N2, N3 and the baseline, applying the multi-scale kernel significantly enhances the classification performance of the model in the spatial feature extraction. In other words, our proposed HPConv benefits the model much more than the PyConv.

To further explore why our HPConv can outperform the baseline model and the PyConv, we retrain the baseline and N1 using word boundary offered by [16]. The results are denoted as N5 and N6, respectively. The major difference is only on applying average based consensus or self-attention based consensus on the frames which are related the annotated word. By comparing N5 with N6, we find that, in the situation of manual word boundary is used, self-attention based consensus basically does not work. This may result from that, the attention weight is a learned ”soft word boundary”. It does the similar thing as manual word boundary, but not as accurate.

4.2. Discussion about Proposed Self-attention Based Consensus

One of the most significant differences between our method and previous methods is the proposed self-attention based consensus. It ensures that the model pays more attention on the relevant frames during classification. To verify its effectiveness, we present the result of the model using only the self-attention based consensus in Table 2 (denoted by N1). Compared with N1 and the baseline, we can say that the self-attention based consensus improves the classification performance.

To further explore why our self-attention based consensus can outperform the average based consensus, we retrain the baseline and N1 using word boundary offered by [16]. The results are denoted as N5 and N6, respectively. The major difference is only on applying average based consensus or self-attention based consensus on the frames which are related the annotated word. By comparing N5 with N6, we find that, in the situation of manual word boundary is used, self-attention based consensus basically does not work. This may result from that, the attention weight is a learned ”soft word boundary”. It does the similar thing as manual word boundary, but not as accurate.

To verify our assumption, we categorize the all test samples by the edit distance of the manual word boundary and the learned word boundary, and count the number of samples and classification accuracy of each category. For the average based consensus, the learned word boundary $B_{avg} = [1, \cdots, 1]^T \in \mathbb{R}^T$. For the self-attention based consensus, the learned word $B_{att} = u(\sum_{n=0}^{N-1} H_n/N - \alpha)$, where $u(\cdot)$ is the unit step function and the threshold constant $\alpha = 0.01$.

The statistical results of the baseline and N1 are shown in Fig. 6 and Fig. 7. From these two figures, we conclude that accuracy is dropping with the increasing of the edit distance and the self-attention based consensus can learn a more precise word boundary.
5. CONCLUSION

In this work, we have presented the HPConv and the self-attention based consensus, replacing the standard convolution and the average based consensus most commonly used in lip-reading models, respectively. Extensive experiments and analysis empirically validate that our proposed HPConv improve the model’s perception of slight lip movements and the self-attention based consensus ensure the model pay more attention to the relevant frames. Combining them results in a new SOTA performance.

6. REFERENCES

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