A COMPARISON OF TRANSFORMER, CONVOLUTIONAL, AND RECURRENT NEURAL NETWORKS ON PHONEME RECOGNITION

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ABSTRACT

Phoneme recognition is a very important part of speech recognition that requires the ability to extract phonetic features from multiple frames. In this paper, we compare and analyze CNN, RNN, Transformer, and Conformer models using phoneme recognition. For CNN, the ContextNet model is used for the experiments. First, we compare the accuracy of various architectures under different constraints, such as the receptive field length, parameter size, and layer depth. Second, we interpret the performance difference of these models, especially when the observable sequence length varies. Our analyses show that Transformer and Conformer models benefit from the long-range accessibility of self-attention through input frames.

Index Terms— Transformer, Conformer, CNN, RNN, Phoneme recognition

1. INTRODUCTION

The ability to extract phonologically meaningful features is essential for various speech processing tasks such as automatic speech recognition (ASR) [1], [2], [3], speaker verification [4], and speech synthesis [5], [6]. Such phoneme-awareness is a fundamental building block for human intelligence; not only the spoken but also the written language directly corresponds to the combination of phonemes.

In speech processing, DNN architectures can be categorized by how the feature extraction mechanism incorporates past and future information. First, convolutional neural networks (CNNs) exploit the fixed-length convolution kernel to aggregate multiple frame information. Because each frame can only access nearby frames within the kernel size in a convolutional layer, CNN models often stack multiple layers to capture long-range relationships. Second, recurrent neural networks (RNNs) compress the entire past/future sequence into a single feature vector. This compression enables RNN to utilize the entire sequence efficiently; however, RNN suffers from the loss of long-range information because the representation space is restricted to a single vector. In contrast, Transformer-based models process the entire sequence simultaneously using the self-attention, where each frame directly accesses every other frame and adaptively determines their importance [7]. In other words, Transformer-based models are more advantageous for long-range dependency modeling compared to CNN and RNN models. For this reason, Transformer has become the universal choice for state-of-the-art speech processing in recent years. However, phoneme recognition is considered a task that depends on a very short time interval of speech when compared to linguistic processing. Many phonemes can be classified even with only one or a few frames of speech. Thus, the phoneme classification efficacy of DNNs, especially Transformer-based ones that can process long-range relationships, needs to be studied in detail.

In this paper, we compare four different DNN architectures for phoneme recognition. Specifically, we compare CNN, RNN, Transformer, and Conformer [3] models under the same conditions. Then, we analyze how different components and limitations of each architecture affect the performance. We emphasize that phoneme recognition is the most suitable task for evaluating the phonetic feature extraction capability. This is because other speech-related tasks usually require a model to encapsulate more information than phonetic knowledge in features. For example, for end-to-end speech recognition, the model should utilize phonetic and linguistic information together to generate correct transcription [8]. For speaker verification, speaker diarization, and speech synthesis, the model must consider the non-phonetic aspects of the speech, such as pitch, accent, speed, or loudness. On the other hand, phoneme recognition performance can be easily measured by accuracy, and the result solely depends on the feature quality.

We summarize our findings below:

• Although each phoneme is uttered within a short period, the phoneme recognition accuracy of DNN is improved until the receptive field length is fairly long.

• When the receptive field length becomes longer, Transformer and Conformer show consistent performance improvement, in contrast to CNN.

• When the parameter size is very small, such as 1M, the ContextNet performs best. Also, ContextNet is advantageous when considering the inference time in GPU.
2. RELATED WORK

2.1. Phoneme recognition

Earlier studies have first introduced neural networks for phoneme recognition [9], such as time-delay networks [10] and bidirectional LSTM [11]. In these works, the benefit of considering more than about 10 frames was marginal.

Recently, phoneme recognition is widely used as a tool to evaluate the amount of phonetic information of DNN features learned from other tasks, including ASR and self-supervised learning. For example, Mockingjay [12], wav2vec 2.0 [13] and wav2vec-U [14] exploit phoneme recognition on self-supervised pre-trained Transformer models to demonstrate that their models learn general speech representations. Our work is different from these works in that we directly train models on the phoneme recognition task. By doing so, the model can fully utilize its capability in extracting phonetic characteristics without being distracted by other objectives.

2.2. Transformer-based speech processing

Several studies have investigated the behavior of Transformer models in order to understand their superior performance. Probing experiments on the self-supervised Transformer models discovered that Transformers detect diverse aspects of audio, including voice pitch, fluency, duration, and phonemes [15, 16, 17]. On the other hand, analyses on the attention map revealed that Transformer considers the entire sequence in phonetic feature extraction, named phonetic localization [8]. For example, a self-attention head that performs phonetic localization would pay high attention weight for similarly pronounced frames.

Furthermore, different self-attention heads are specified for different phonetic relationships [8, 19]. Specifically, phonetic self-attention behavior can be separated into similarity-based and content-based ones, where the former focuses on the pairwise similarity of frames while the latter considers the content of each frame [19]. We note that such unique behaviors have not been reported in CNN- and RNN-based models.

2.3. Comparison between Transformer and Others

Extensive studies have been conducted to compare CNN to Transformers in the vision domain [20]. Especially, comparisons between vision Transformer (ViT) and CNN show that they learn very different aspects of an image [21]; for example, ViT and CNN behave as low-pass and high-pass filters, respectively [22]. However, in-depth analyses were not conducted much in the speech domain. Several works have investigated RNN-based and Transformer-based models for ASR tasks [23, 24, 25], but only the final word error rate and training dynamics are compared. In our experiments, we carefully design model configurations for a fair comparison and compare four architectures with the same constraints.

3. DNN ARCHITECTURE

3.1. CNN

We choose ContextNet [2] as a baseline because the ContextNet block has been employed in many state-of-the-art CNN-based ASR models [2, 26]. ContextNet architecture differs from other CNNs in two components: depthwise separable (DS) convolution [27, 2, 26, 28] and squeeze-excite (SE) module [29]. Figure 1 shows one ContextNet block that includes four DS convolution layers, residual connection, and SE module. Note that we take a block as the basic unit of ContextNet for experiments.

First, DS convolution includes a depthwise convolution of large kernel size followed by a pointwise convolution of kernel size 1. The former aggregates neighboring frames without mixing channels, and the latter combines every channel for each frame. This two-step process makes DS convolution parameter-efficient because the model can increase the kernel size without increasing the number of parameters much. Second, SE module adaptively re-weights channels based on the per-channel feature averaged through the entire sequence. SE module is an efficient approach for incorporating the global information in feature processing, however, it does not consider the difference of frames because the same channel weights are multiplied by every frame feature.

3.2. RNN

We use LSTM [30] as our default RNN layer. Specifically, we stack multiple bidirectional LSTM layers to build an RNN model [1]. Unlike other architectures, RNN-based models require sequential processing of frames, which causes a slow inference especially for bidirectional ones.

3.3. Transformer

We employ the pre-norm Transformer layer [31] which includes two submodules: multi-head self-attention and feed-forward. Please refer to the original work [7] for the internal structure of submodules. While the post-norm design was employed in the original Transformer model, the pre-norm design is adopted in many speech and language processing models [3, 32].
3.4. Conformer

We utilize the Conformer layer [3], which is widely adopted in recent state-of-the-art ASR models [33, 34]. The key idea of Conformer is to incorporate an additional convolution module between the self-attention and feed-forward submodules. Due to this convolution module, Conformer can enhance the locality in extracted features.

4. PHONEME RECOGNITION

In this section, we compare various models from three perspectives: 1) receptive field length, 2) parameter size, and 3) layer depth. For a fair comparison, we change each aspect while preserving the others.

First, we vary the receptive field length to measure information efficiency. The receptive field length represents how many frames incorporate in the feature extraction process. Note that ContextNet with SE module [29] and LSTM cannot restrict the receptive field since these modules are designed to observe the entire sequence. Second, we change the number of layers to investigate the trade-off between the depth and hidden dimension, or the depth and receptive field length, while maintaining the parameter size. Finally, we compare different models with the same number of parameters to measure parameter efficiency.

4.1. Setup

We train the models on the LibriSpeech-960 [35] dataset using the frame-level phoneme alignment extracted from Montreal Forced Aligner [36]. We use the 37 phoneme classes taken from the previous study [8], including ‘silence’. We utilize 80-dimensional Mel filterbank features as the input, extracted by 25ms window and 10ms stride.

Figure 2 illustrates the common architecture for models used in phoneme recognition experiments. The input features first pass through two convolutional subsampling layers [1] of kernel size 3 and stride 2, in order to efficiently reduce the number of frames without much information loss. For the loss function, a simple per-frame cross-entropy is used.

The models are trained using AdamW [37] optimizer for 25K iterations with the maximum learning rate of 0.001, weight decay of 0.001, and cosine learning rate decay schedule. The batch size is set to 128, and SpecAugment [38] is employed for regularization. The same training configuration is applied for every experiment.

4.2. Effect of the Receptive Field Length

To investigate the effect of the receptive field length, we fix the number of parameters to 5M and set the number of layers to four. For ContextNet, we either 1) set the number of blocks to four and change the convolution kernel size, or 2) stack more blocks without increasing the kernel size. For Transformer and Conformer, we manually restrict the accessible self-attention range by masking the attention map. For example, the receptive field length of CNN with four DS convolutional layers (i.e., a single ContextNet block) of kernel size \( k \) is \( 4k - 3 \), which can be matched by restricting the self-attention range to \([−r, r] = [−2k + 2, 2k − 2]\).

Table 1 and 2 show the accuracy of four different DNN architectures. ‘ContextNet/SE’ indicates that the SE module is removed to prevent incorporating the global information of the entire sequence. To equally set the parameter size, the hidden dimension of ContextNet(\( l = 4 \)), LSTM, Transformer, and Conformer is set to 352, 336, 248, and 192, respectively. We find out several interesting results:
The parameter size is about 5M for all models. The benefit of increasing the number of layers in Transformer and Conformer is higher than in the other two architectures. The effect of the layer depth for ContextNet/SE is shown in Table 3 and that for the RNN, Transformer, and Conformer is presented in Table 4. Since one ContextNet/SE layer contains four DS convolution layers, the ContextNet/SE with \( l = 16 \) actually connects 64 DS convolution layers in series. As expected, utilizing more layers improves the accuracy without exception. We summarize our findings as below:

- The benefit of increasing the number of layers in Transformer and Conformer is higher than in the other two architectures.

- Conformer achieves the highest parameter efficiency when using more than 4 layers. For example, the 4-layer Conformer model already achieves higher accuracy than other 8-layer models.

### Table 2: Phoneme recognition accuracy (%) of ContextNet models with different receptive field lengths and layer depths.

| Model         | Receptive field (sec) | test-clean | test-other |
|---------------|-----------------------|------------|------------|
| Context(\(k = 3, l = 4\)) | 1.32*                 | 89.5       | 83.3       |
| Context(\(k = 5, l = 4\)) | 2.60*                 | 89.7       | 83.8       |
| Context(\(k = 9, l = 4\)) | 5.16*                 | 89.7       | 83.7       |
| Context(\(k = 17, l = 4\)) | 10.28*                | 89.6       | 83.4       |
| Context(\(k = 33, l = 4\)) | 20.52*                | 89.4       | 83.0       |

| Model         | Receptive field (sec) | test-clean | test-other |
|---------------|-----------------------|------------|------------|
| Context/SE(\(k = 3, l = 4\)) | 1.32                  | 89.1       | 82.1       |
| Context/SE(\(k = 5, l = 4\)) | 2.60                  | 89.4       | 82.7       |
| Context/SE(\(k = 9, l = 4\)) | 5.16                  | 89.5       | 82.8       |
| Context/SE(\(k = 17, l = 4\)) | 10.28                 | 89.4       | 82.8       |
| Context/SE(\(k = 33, l = 4\)) | 20.52                 | 89.4       | 82.7       |

| Model         | Receptive field (sec) | test-clean | test-other |
|---------------|-----------------------|------------|------------|
| Context(\(k = 5, l = 4\)) | 2.60                  | 89.4       | 82.7       |
| Context(\(k = 5, l = 8\)) | 5.16                  | 89.8       | 83.3       |
| Context(\(k = 5, l = 12\)) | 10.28                 | 89.7       | 83.3       |
| Context(\(k = 5, l = 16\)) | 20.52                 | 89.6       | 83.2       |

- LSTM shows the worst performance although its theoretical receptive field length is unlimited. This observation is consistent with every experiment.

- Transformer and Conformer benefit from increasing the receptive field length, but the accuracy of ContextNet saturates from a certain point. The best performance for CNN models is achieved with a receptive field length of 5.16 seconds.

- Transformer with unlimited receptive field length is worse than Conformer with the shortest length, emphasizing the importance of convolutional layers in phonetic feature extraction.

In fact, convolution and self-attention extract phonetic information differently by focusing on local and global regions of the sequence, respectively. A recent study discovered a behavior called **phonetic localization** that the self-attention module captures the phonetic relationship through the entire sequence. For example, in self-attention, a frame tends to pay larger attention weights to similar phonemes (e.g., ‘TH’ to ‘SH’, ‘N’ to ‘M’, ‘S’ to ‘Z’). Similar frames affect each other in the feature domain, and as a result, they become more clustered based on phoneme classes.

Considering that the same phoneme can be pronounced differently, it is advantageous to standardize features of the same class for phoneme recognition. The essence of phonetic localization is that every frame can access all frames dynamically. When similar frames appear in the sequence broadly, self-attention can aggregate such related information regardless of the distance between frames, while convolution cannot utilize the phonetic connection between far frames. We believe the phonetic localization is the reason why the accuracy improves as the receptive field length increases for models that equip self-attention.

### 4.3. Effect of the Number of Layers

It is known that utilizing multiple layers helps extract more complex and rich features. On the other hand, a larger hidden dimension is often considered to provide better expressiveness for each frame feature. Therefore, increasing the width(hidden dimension) or the depth(number of layers) is an interesting design choice. In this subsection, we increase the number of layers while preserving the parameter size (5M) and receptive field length. Specifically, we decrease the hidden dimension as the number of layers increases.

The effect of the layer depth for ContextNet/SE is shown in Table 2 and that for the RNN, Transformer, and Conformer is presented in Table 3. Since one ContextNet/SE layer contains four DS convolution layers, the ContextNet/SE with \( l = 16 \) actually connects 64 DS convolution layers in series. As expected, utilizing more layers improves the accuracy without exception. We summarize our findings as below:

- The benefit of increasing the number of layers in Transformer and Conformer is higher than in the other two architectures.

- Conformer achieves the highest parameter efficiency when using more than 4 layers. For example, the 4-layer Conformer model already achieves higher accuracy than other 8-layer models.
Table 4: Phoneme recognition accuracy (%) of DNN models with different parameter sizes. The layer depth is set to two, and every model utilizes unlimited receptive field length.

| Model          | Parameter size (M) | test-clean | test-other |
|----------------|--------------------|------------|------------|
| Context(d = 248) | 1.04               | 86.8       | 79.0       |
| Context(d = 416) | 3.09               | 88.6       | 81.9       |
| Context(d = 448) | 5.04               | 89.0       | 82.4       |
| LSTM(d = 240)   | 1.05               | 82.6       | 73.2       |
| LSTM(d = 392)   | 3.02               | 83.4       | 74.2       |
| LSTM(d = 432)   | 5.07               | 83.3       | 74.0       |
| Trans(d = 168)  | 1.00               | 83.7       | 75.2       |
| Trans(d = 288)  | 3.06               | 85.7       | 77.6       |
| Trans(d = 328)  | 5.09               | 85.9       | 77.8       |
| Conf(d = 128)   | 1.01               | 86.1       | 78.6       |
| Conf(d = 216)   | 2.97               | 88.5       | 81.7       |
| Conf(d = 256)   | 5.08               | 88.9       | 82.2       |

4.4. Effect of the Parameter Size

To evaluate the relationship between the parameter size and phoneme feature extraction, we change the hidden dimension $d$ of each model and compare the accuracy. For ContextNet and Conformer, the convolution kernel size is set to $k = 9$ as in Table 4. Note that ContextNet models in this experiment observe the entire sequence by utilizing the SE module.

Table 4 compares DNN architectures with the same parameter budget. In particular, we evaluate the models with a small parameter size to assume an environment with very limited resources. For 1M, 3M, and 5M size models, the number of channels in the convolutional subsampling (see Figure 2) is set to 64, 128, and 256, respectively. We observe that ContextNet and LSTM are the best and the worst parameter-efficient architecture in this small parameter size configuration with two layers. However, when the layer depth is 4 (see Table 1), Conformer achieves higher accuracy than ContextNet with the same receptive field length and parameter size. This implies that the advantage of ContextNet in parameter efficiency may disappear for modern DNN architectures that stack many layers.

5. ANALYSIS

5.1. Depth-separable and Squeeze-Excite

As explained in Section 3.1, ContextNet exploits two specially designed components, DS convolution and SE module. We conduct an ablation study on these modules to evaluate the effect of each ingredient in phonetic feature extraction. When removing the DS convolution, we replace the cascading two convolution layers, depthwise and pointwise convo-

Table 5: Ablation of depth separable (DS) convolution and SE module for phoneme recognition. The layer depth is fixed to two.

| Model          | DS | SE | Params | test-clean | test-other |
|----------------|----|----|--------|------------|------------|
| Context(d = 352) | ✓  | ✓  | 5M     | 89.7       | 83.8       |
| Context(d = 352) | ✓  | ✗  | 5M     | 89.4       | 82.7       |
| Context(d = 200) | ✗  | ✓  | 5M     | 89.4       | 83.1       |
| Context(d = 200) | ✗  | ✗  | 5M     | 89.1       | 82.1       |
| Context(d = 352) | ✓  | ✓  | 13M    | 90.6       | 85.0       |
| Context(d = 352) | ✓  | ✗  | 13M    | 90.3       | 84.1       |

Table 5 demonstrates the importance of the DS convolution and SE module for ContextNet, using a 5M parameter size budget and a layer depth of two. In summary, the combination of DS convolution and SE module is the most parameter-efficient configuration. In addition, the accuracy loss caused by replacing DS convolution with full convolution ($-0.7\%$) is smaller than removing the SE module ($-1.1\%$) in test-other dataset. When the hidden dimension is not reduced, the model achieves the best accuracy as expected, at a cost of about 2.6 times more parameters.

5.2. The Number of Self-Attention Heads

Increasing the layer depth improves the accuracy (see Table 3), but this also increases the total number of (self-)attention heads. To clarify the source of improvement, we conduct an ablation study on the number of heads; we vary the number of heads to 2, 4, 8, and 16. Note that changing the number of self-attention heads in a Transformer and Conformer layer does not affect the number of parameters because the per-head hidden dimension changes accordingly. Transformer and Conformer models in previous experiments employ four heads for every layer regardless of the hidden dimension.

Table 6 presents the effect of the number of attention heads in phoneme recognition. We observe that accuracy consistently increases as the number of heads increases. We assume that the improvement is because more diverse phonetic relationships can be captured from one layer [8], especially for the challenging test-other dataset. The results also show that increasing the number of layers (4 heads, 4 layers) achieves higher accuracy than increasing the number of heads (8/16 heads, 2 layers).
Table 6: Ablation on the number of self-attention heads for phoneme recognition.

| Model               | #Head | #Layer | test-clean | test-other |
|---------------------|-------|--------|------------|------------|
| Trans \((d = 328)\) | 2     | 2      | 85.0       | 76.9       |
| Trans \((d = 328)\) | 4     | 2      | 85.9       | 77.8       |
| Trans \((d = 328)\) | 8     | 2      | 86.9       | 79.1       |
| Trans \((d = 320)\) | 16    | 2      | 87.2       | 79.4       |
| Trans \((d = 248)\) | 4     | 4      | 88.4       | 81.4       |
| Conf \((d = 256, k = 17)\) | 2     | 2      | 88.8       | 82.1       |
| Conf \((d = 256, k = 17)\) | 4     | 2      | 88.9       | 82.2       |
| Conf \((d = 256, k = 17)\) | 8     | 2      | 89.2       | 82.6       |
| Conf \((d = 256, k = 17)\) | 16    | 2      | 89.3       | 82.7       |
| Conf \((d = 192, k = 9)\) | 4     | 4      | 90.3       | 84.4       |

Table 7: Transferability of attention range restriction through different training and inference setting.

(a) test-clean accuracy (%)

| Train \(r\) \| Inference \(r\) | 12 | 28 | 60 | unlimited |
|-----------------------------|----|----|----|-----------|
| Conf \((r = 12)\)           | 89.5 | 89.0 | 88.3 | 87.7      |
| Conf \((r = 28)\)           | 89.4 | 89.7 | 89.7 | 89.4      |
| Conf \((r = 60)\)           | 89.0 | 89.6 | 89.8 | 89.7      |
| Conf \((unlimited)\)        | 87.4 | 89.0 | 89.6 | 90.3      |

(b) test-other accuracy (%)

| Train \(r\) \| Inference \(r\) | 12 | 28 | 60 | unlimited |
|-----------------------------|----|----|----|-----------|
| Conf \((r = 12)\)           | 83.0 | 82.2 | 81.4 | 80.7      |
| Conf \((r = 28)\)           | 83.1 | 83.5 | 83.5 | 83.1      |
| Conf \((r = 60)\)           | 82.5 | 83.4 | 83.8 | 83.7      |
| Conf \((unlimited)\)        | 79.8 | 82.6 | 83.6 | 84.4      |

5.3. Transferability of Restricted Attention Range

For Transformer and Conformer models, we can think of using different self-attention ranges for training and inference. In other words, is the attention range restriction generally transferable? For example, the model may access only 10 seconds of receptive field length during training but observe an unlimited range during inference.

Table 7 shows the accuracy of Conformer models that exploit different attention range restrictions for training and inference. The model configuration follows Table 1. In short, the model best performs with the same range restriction used during training. The performance degradation grows as the difference between \(r\) used in training and inference increases. Furthermore, the model trained with an unlimited attention range suffers the most from restricting the attention range. We assume this is because such model is trained to exploit global information more than the local characteristics.

5.4. Inference Speed

The number of parameters is an important factor for practical usage, but the inference speed does not directly correspond to the parameter size. We measure the GPU inference speed of different architectures and find out in which situation each architecture is advantageous.

Figure 3 shows the inference speed of the encoder part, the middle block in Figure 2, estimated on a single A100 GPU. The models in Figure 3 are the best models in Table 1. Note that the parameter size of models is almost the same (5M). During inference, we fix the batch size to 64 and only change the input sequence length. We observe that ContextNet and LSTM models show linearly increasing inference time of \(O(T)\), while Transformer and Conformer show quadratically increasing time of \(O(T^2)\). Especially, ContextNet is significantly faster when the input sequence length is longer than 10 seconds. We assume this is mainly due to the efficient DS convolution. Conformer is slightly slower than Transformer because of an additional convolution module; however, as the sequence length increases, the gap decreases as the proportion of self-attention computation increases.

6. CONCLUSION

We presented a comparative study of various DNN architectures through the lens of phoneme classification. We compared CNN, RNN, Transformer, and Conformer models from three different perspectives. The performance of CNN saturates when the receptive field length exceeds about 5 seconds, but Transformer and Conformer continue to increase in performance. This is because they employ the self-attention mechanism to cluster and utilize similar phonemes at a distance. When the parameter size allowed is small, such as 1M, the ContextNet performs best. In addition, the ContextNet is very advantageous in inference speed.
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