MANNER OF ARTICULATION DETECTION USING CONNECTIONIST TEMPORAL CLASSIFICATION TO IMPROVE AUTOMATIC SPEECH RECOGNITION PERFORMANCE

Pradeep R and Sreenivasa Rao K
Department of Computer Science and Engineering, Indian Institute of Technology, Kharagpur, India
{pradeep.raj31, ksrao}@iitkgp.ac.in

ABSTRACT

Conventionally, the manner of articulations in speech signal are derived using discriminative signal processing techniques or deep learning approaches. However, training such complex systems involves feature extraction, phoneme force alignment and deep neural network training. In our work, we initially detect the manner of articulations without phoneme alignment using an end-to-end manner of articulation modeling based on connectionist temporal classification (CTC). The manner of articulation knowledge is deployed in the conventional character CTC path to regenerate the new character CTC path. The modified manner based character CTC is evaluated on open source speech datasets such as AN4, LibriSpeech and TEDLIUM-2 and it outperforms over the baseline character CTC.

Index Terms— Manner of articulation, connectionist temporal classification, speech recognition

1. INTRODUCTION

Automatic speech recognition (ASR) has emerged as one of the active areas of technology with a lot of research and development efforts mainly in speech processing communities. The conventional acoustic models (AMs) of an ASR system followed a generative approach based on Hidden Markov Models (HMMs) [1] where the emission probabilities of each state were modeled with a Gaussian Mixture Model (GMM). Later, the performance of ASR has been improved dramatically by the introduction of deep neural networks (DNNs) as acoustic models [2] [3]. In the hybrid HMM/DNN approach, DNNs are used to classify speech frames into clustered context-dependent (CD) states (i.e., senones). On a variety of ASR tasks, DNN models have shown significant gains over the GMM models. However, the HMM-GMM or HMM-DNN pipelines are highly complex as it involves multiple training strategies (such as CI phones, CD senones), various parameters (such as dictionaries, decision trees) and the performance depends on optimal choice of number of senones, Gaussians, etc.

More recent work has been focused on solutions which involves a simple paradigm which come close to end-to-end systems. On this aspect, Graves et al. [4] introduced the connectionist temporal classification (CTC) objective function to infer speech-label alignments automatically without having to rely on an alignment between the audio sequence and the symbol sequence. This CTC technique is further investigated in [5] [6] on large-scale acoustic modeling tasks. On the other hand, the attention-based method [7] exploits an attention mechanism to perform alignment between acoustic features and recognized symbols. However, the basic temporal attention mechanism is too flexible in the sense that it allows extremely non-sequential alignments. This is rational for applications such as machine translation where input and output word order are different [8]. However in phone attribute detection, the acoustic features and the corresponding outputs proceed in a monotonic way. Since CTC permits an efficient computation of a strictly monotonic alignment using dynamic programming, we propose to train a CTC-based manner of articulation detector to detect vowels, semi-vowels, nasals, fricatives and stop consonants.

Speech attributes were detected using discriminative features at the front-end and training the classifier [9]. Signal processing approaches are used for automatic and accurate detection of the closure-burst transition events of stops and affricates [10]. Later deep learning techniques were used to detect speech attributes [11]. However, training such complex systems involves feature extraction, phoneme force alignment and deep neural network training. Recently, Cernak et al., [12] exploited a solution to train a nasal sound detector without phone alignment using an end-to-end phone attribute modeling based on the connectionist temporal classification.

Recent success on nasal detection using CTC motivated us to extend their framework for detecting five broad manners of articulation namely vowel, semi-vowel, nasal, fricative and stop consonant. In the first part of our work, we extend CTC based nasal and non-nasal detection framework [12] to detect five broad manners of articulation. Later, we propose a mech-
anism where the manner of articulation detection knowledge is deployed in decoding a speech utterance and study its impact in ASR performance. The main addressed question of this work was if it is possible to train a CTC manner detector without phone alignment and embed this knowledge in ASR decoding.

2. MANNER OF ARTICULATION DETECTION USING CTC

The character level transcripts are mapped to five different manners of articulation \{V, $, N, F, S\} that represents vowel, semi-vowel, nasal, fricative and stop consonant respectively. Figure 1 illustrates a toy example of obtaining manner of articulation labels from the character labels. The connectionist temporal classification (CTC) approach \cite{15} is an objective function that allows an end-to-end training without requiring any frame-level alignment between the input and target labels. It introduces an intermediate representation called the CTC path. The label sequence can be represented by a set of all the possible CTC paths that are mapped to it.

For an input sequence \( X = (x_1, ..., x_T) \), the conditional probability \( P(z|X) \) is then obtained by summing over all the probabilities of all the paths that correspond to the target label sequence \( y \) after inserting the repetitions of labels and the blank tokens, i.e.,

\[
P(z|X) = \sum_{y'} P(y'|X) = \sum_{y' \in \phi(z)} \prod_{t=1}^{T} P(y_t'|x_t)
\]

where \( \phi(z) \) denotes the set of all possible paths that correspond to \( z \) after repetitions of labels and insertions of the blank token. The conditional probability of the labels at each time step, \( P(y_t|x_t) \), is generally estimated using a RNN (LSTM/GRU). The model can be trained to maximize Equation 1 by using gradient descent, where the required gradients can be computed using the forward-backward algorithm \cite{16}.

In order to detect manners of articulation using CTC, the softmax output nodes are set to \( M+k \) where \( M \) is the number of manners and \( k \) characters are added to include blank (\('<') or space (\('>'). The manner of articulation detector using CTC is shown in left part of Figure 2. The bottom of the network is two layers of convolutions over both time and frequency domains. Temporal convolution is commonly used in speech processing to efficiently model temporal invariance for variable length utterances. Convolution in frequency attempts to model spectral variance due to speaker variability and it has been shown to further improve the performance \cite{13}. Following the convolutional layers are bidirectional recurrent layers. After the bidirectional recurrent layers, a fully connected layer is applied and the output is produced through a softmax function computing a probability distribution over the target labels blank, vowel, semi-vowel, nasal, fricative, stops, space. The model is trained using the CTC loss function. To accelerate the training procedure, Batch Normalization \cite{14} is applied on hidden layers.

3. CHARACTER CTC DERIVED FROM MANNER OF ARTICULATION CTC

We separately train manner of articulation CTC detector and the conventional character based CTC detector. Figure 3 shows the overview of obtaining character CTC by combining the manner of articulation posteriors and the baseline character posteriors.

3.1. Modified character CTC

The basic version of obtaining manner based character CTC is shown in Algorithm 1. The modified character index is initialized with blank labels (line 4) and the previous most probable character index is initialized with space index (5). Then, we find the frame level index by calculating the most probable manner of articulation portions obtained from posteriors manner, \( \text{postManner} \) (6). We find the non-blank index, \( nBInx \) in the manner CTC and their start and end frame durations, \( nBSeg \) (7). The algorithm iterates over all non-blank portions obtained from the manner CTC. We iteratively find the index of the most probable character segment by forcing the blank probabilities to zero (9). This is to ensure that the non-blank segment derived from manner CTC always emits a non-blank character. Later, in the non-blank manner segments, we find the most probable characters and are sorted according to the frequency of occurrence \( \text{sort}_f \) within the manner alignments (10). In the next phase, we find the characters excluding the previous index so that a new symbol is generated. We compare the current character generated for a manner peak with the previous character index and is ensured that the current character is always new as compared to the previous character (11-12). The current index now acts as a previous index.
and the process is repeated for all frames (13). After the last
time-step, the best character indices are converted to character
symbols and is returned as a result (14-15). The basic idea
of the proposed method is to observe the non-blank peaks in
the manner CTC and it is forced to emit a non-blank symbol
for representing blank and space characters. The most probable manner index at frame level is shown
in Figure 3(b). We initialize the manner based CTC character
to blank symbols as shown in Figure 3(c). Figure 3(d)
shows the sorted list of character indices for each frame based
on character posterior probabilities. They are generated using
baseline character CTC detector. We denote the characters
$C_1$ and $C_{29}$ for representing blank and space characters respectively for illustration and $C_{2}-C_{28}$ for representing non-blank
characters. The greedy search on these character probabilities
picks up the most probable character index at each frame and
it is represented in Figure 3(e). The decoded sequence generated
using best path decoding or greedy search is $C_4C_{29}C_{10}$.

We find the start and end frame index of manner CTC
peak. If the manner CTC emits a non-blank symbol, then
the character CTC is forced to emit a non-blank character.
This can be achieved by iteratively finding the most probable
element in decreasing order of the posteriors probabilities
and finding the optimal character by sorting the characters
according to their frequency of occurrence in each segment. For
instance $m_1$ is the most probable manner index and the cor-
responding character index is $c_1$ which is a blank symbol. So
we find the second maximum character indices and sort them
according to their frequency of occurrence and hence emit a
single non-blank symbol. We will also compare the current
index emitted with the previous index and if both are same
then we emit different index by choosing appropriate sym-
bol. The most probable manner index at frame level is shown
in Figure 3(b). We initialize the manner based CTC characters
to blank symbols as shown in Figure 3(c). Figure 3(d)
shows the sorted list of character indices for each frame based
on character posterior probabilities. They are generated using
baseline character CTC detector. We denote the characters $C_1$
and $C_{29}$ for representing blank and space characters respectively for illustration and $C_{2}-C_{28}$ for representing non-blank
characters. The greedy search on these character probabilities
picks up the most probable character index at each frame and
it is represented in Figure 3(e). The decoded sequence generated
using best path decoding or greedy search is $C_4C_{29}C_{10}$.

4. EXPERIMENTS

We used three open source databases for training the manner
and character CTC systems: (1) AN4[^1] - the database con-
tains alpha numeric speech data having 948 training and 130
test utterances. The dataset provides a good sample to achieve
deterministic results to scale up with larger datasets. (2) Lib-
riSpeech[^2] - the data are sampled at 16 kHz, and the training
part of the corpus are with size approximately 100, 360 and
490 hours respectively. In our experiments, we use 100 hours
train-clean corpus. (3) TEDLIUM-2[^3] - the English-language TED talks, with transcriptions, sampled at 16kHz. It contains
about 118 hours of speech.

![Fig. 3. (a) Manner of articulation predicted labels using man-
ner CTC detector (b) Most probable manner index at frame level
(c) New character index initialization to blank symbols
(d) Sorted character indices obtained using character CTC
detector for each frame (e) Most probable character index
using state-of-the art character CTC detector (f) Character
indices derived from manner of articulation CTC detector
manner of articulation. We denote the most probably pre-
dicted blank symbols in black color and space character by
dotted rectangle for illustration. We consider only those por-
tions where the manner CTC detector emits non-blank sym-

-----------------

[^1]: http://www.speech.cs.cmu.edu/databases/an4/
[^2]: http://www.openslr.org/resources/12/
[^3]: http://www.openslr.org/7/
[^4]: https://github.com/SeanNaren/deepspeech.pytorch
and the character error rate (CER) obtained using the baseline and the proposed method. The pre-trained manner of articulation models and the baseline CTC models trained with AN4 dataset is made as an open source code. It is observed that the manner of articulation knowledge in modifying the CTC path has significant impact in improving the performance of ASR.

5.1. Discussion

The CNN in the used model performed 2D convolution, where the first dimension is frequency and the second dimension is time. A longer stride is usually applied to speed-up training. Using the stride in the time dimension results into time compacting of the input audio, e.g., using the stride of 2 results into 2 times less frames of the output. For applications where time alignment is required, we experimented with the stride of 1 and we observed the convergence in training. Figure 4 shows an example of the label index generated on manner CTC, baseline character CTC and the modified manner based character CTC detector. The speech utterance is from AN4 test dataset (test/an4/wav/cen8 − fcvw − b.wav) whose content has the sentence “ELEVEN TWENTY SEVEN FIFTY SEVEN”. The most probable manner index is derived from the posterior manner as shown in Figure 4(a). On top of the figure we illustrate some of the text transcript portions. The baseline character CTC as shown in Figure 4(b) generates “E NEN TWENTY SEVEN FIFTY SEVEN” leading to false insertion and substitution errors. The non-blank portions in the manner peaks are forced to generate non-blank characters derived from character CTC detector using proposed method. The manner of articulation based character CTC generates the optimal character labels as per the peakiness in the manner portions. Figure 4(c) shows the modified character index. The decoded sequence obtained using proposed method is : “EREVEN TWENTY SEVEN FIFTY SEVEN”. It can be observed that the additional space that was generated using baseline method is nullified using the proposed method. Also the blank character probabilities that dominated to miss out the substring ‘EVEN’ is recovered. The generation of the character ‘R’ may be due to the fact that the manner of articulation has semivowel. The probability of occurrence of L is less than that of R.

6. CONCLUSION

This paper has proposed to use the connectionist temporal classification for the end-to-end manner of articulation modeling. The manner of articulation knowledge is deployed in the conventional character CTC path to regenerate the new character CTC path. The modified manner based character CTC is evaluated on open source speech datasets such as AN4, LibriSpeech and TEDLIUM-2 and it outperforms over the baseline character CTC. Application of the proposed manner of articulation CTC detector in weight adaptation of baseline end-to-end ASR training is also planned for future work.
7. REFERENCES

[1] Geoffrey Hinton, Li Deng, Dong Yu, George E Dahl, Abdel-rahman Mohamed, Navdeep Jaitly, Andrew Senior, Vincent Vanhoucke, Patrick Nguyen, Tara N Sainath, et al., “Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups,” IEEE Signal processing magazine, vol. 29, no. 6, pp. 82–97, 2012.

[2] George E Dahl, Dong Yu, Li Deng, and Alex Acero, “Context-dependent pre-trained deep neural networks for large-vocabulary speech recognition,” IEEE Transactions on audio, speech, and language processing, vol. 20, no. 1, pp. 30–42, 2012.

[3] Andrew L Maas, Peng Qi, Ziang Xie, Awni Y Hannun, Christopher T Lengerich, Daniel Jurafsky, and Andrew Y Ng, “Building dnn acoustic models for large vocabulary speech recognition,” Computer Speech & Language, vol. 41, pp. 195–213, 2017.

[4] Alex Graves, Santiago Fernández, Faustino Gomez, and Jürgen Schmidhuber, “Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks,” in Proceedings of the 23rd international conference on Machine learning. ACM, 2006, pp. 369–376.

[5] Alex Graves and Navdeep Jaitly, “Towards end-to-end speech recognition with recurrent neural networks,” in International Conference on Machine Learning, 2014, pp. 1764–1772.

[6] Hasim Sak, Andrew Senior, Kanishka Rao, Ozan Irsoy, Alex Graves, Françoise Beaufays, and Johan Schalkwyk, “Learning acoustic feature labels for speech recognition with recurrent neural networks,” in Acoustics, Speech and Signal Processing (ICASSP), 2015 IEEE International Conference on. IEEE, 2015, pp. 4280–4284.

[7] Dzmitry Bahdanau, Jan Chorowski, Dmitriy Serdyuk, Philemon Brakel, and Yoshua Bengio, “End-to-end attention-based large vocabulary speech recognition,” in Acoustics, Speech and Signal Processing (ICASSP), 2016 IEEE International Conference on. IEEE, 2016, pp. 4945–4949.

[8] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio, “Neural machine translation by jointly learning to align and translate,” arXiv preprint arXiv:1409.0473, 2014.

[9] Chin-Hui Lee, Mark A Clements, Sorin Dusan, Eric Fosler-Lussier, Keith Johnson, Biing-Hwang Juang, and Lawrence Rabiner, “An overview on automatic speech attribute transcription (asat),” in Eighth Annual Conference of the International Speech Communication Association, 2007.

[10] TV Ananthapadmanabha, AP Prathosh, and AG Ramakrishnan, “Detection of the closure-burst transitions of stops and affricates in continuous speech using the plosion index,” The Journal of the Acoustical Society of America, vol. 135, no. 1, pp. 460–471, 2014.

[11] Sabato Marco Siniscalchi, Dong Yu, Li Deng, and Chin-Hui Lee, “Exploiting deep neural networks for detection-based speech recognition,” Neurocomputing, vol. 106, pp. 148–157, 2013.

[12] Milos Cernak and Sibo Tong, “Nasal speech sounds detection using connectionist temporal classification,” in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2018, pp. 5574–5578.

[13] Tara N Sainath, Abdel-rahman Mohamed, Brian Kingsbury, and Bhuvana Ramabhadran, “Deep convolutional neural networks for lvcsr,” in Acoustics, speech and signal processing (ICASSP), 2013 IEEE international conference on. IEEE, 2013, pp. 8614–8618.

[14] Sergey Ioffe and Christian Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” arXiv preprint arXiv:1502.03167, 2015.

[15] Dario Amodei, Sundaram Ananthanarayan, Rishita Anubhai, Jingliang Bai, Eric Battenberg, Carl Case, Jared Casper, Bryan Catanzaro, Qiang Cheng, Guoliang Chen, et al., “Deep speech 2: End-to-end speech recognition in english and mandarin,” in International Conference on Machine Learning, 2016, pp. 173–182.