MANDARIN TONE MODELING USING RECURRENT NEURAL NETWORKS

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ABSTRACT

We propose an Encoder-Classifier framework to model the Mandarin tones using recurrent neural networks (RNN). In this framework, extracted frames of features for tone classification are fed in to the RNN and casted into a fixed dimensional vector (tone embedding) and then classified into tone types using a softmax layer along with other auxiliary inputs. We investigate various configurations that help to improve the model, including pooling, feature splicing and utilization of syllable-level tone embeddings. Besides, tone embeddings and durations of the contextual syllables are exploited to facilitate tone classification. Experimental results on Mandarin tone classification show the proposed network setups improve tone classification accuracy. The results indicate that the RNN encoderclassifier based tone model flexibly accommodates heterogeneous inputs (sequential and segmental) and hence has the advantages from both the sequential classification tone models and segmental classification tone models.

Index Terms— Tone classification, recurrent neural network, deep learning, speech recognition

1. INTRODUCTION

Tone modeling plays an important role in reducing ambiguity in tonal languages such as Mandarin. Utilization of tone information has proved to be successful in improving accuracy in Mandarin speech recognition, either by appending the pitch related tonal features with the traditional spectral features for acoustic model training [1], which is referred to as embedded tone modeling, or explicitly building tone classifier and adding tone model scores in lattice re-scoring [2]. Explicitly built tone models are also applied to detect erroneous tonal pronunciations in computer-assisted language learning (CALL) [3]. Compared with embedded tone modeling, the explicit tone modeling approach is capable of exploiting the supra-segmental nature of the tones or using better tone classifier to improve system performance.

There are two major approaches to explicit tone modeling: sequence based tone modeling and segment based tone modeling. Sequence based tone models accept sequential observations while the segment based tone models use fixed dimension feature vector. Because articulation of human is temporal and output of pitch-related feature extraction processing is frame based, to model the tones using sequential model is natural and reasonable. The sequenced model can be hidden Markov model (HMM) [4] or hidden conditional random fields (HCRFs) [5], etc. The shortcoming of this

modeling method is that it is difficult for the sequence based models to utilize segment based information from the contextual tones. For example, great efforts are needed to consider the pitch related features of contextual syllable [7]. An alternative to sequence based method is to classify the tones using segmental classifiers such as Gaussian mixture model (GMM) [6], support vector machine (SVM) [8] and neural network (NN) [9]. Besides, stochastic polynomial trajectory model (SPTM) [11], and decision tree based tone classifier [12] have also been tried. Though the proposed methods can be effective, there has to be manually conversion of the temporal observation sequence into fixed dimensional features, which requires expertise and experience and might not get the optimal results.

Recently, the progress in deep learning has shown great success in various applications such as computer vision [13] and speech recognition [14, 15]. Moreover, many recent works showed that neural networks can be successfully used in a number of tasks in natural language processing (NLP), such as machine translation [16], word embedding extraction [17] and sentence classification [18]. For tone modeling, authors in [19] proposed to use DNN as tone classifier with manually designed tone features and obtained better results with traditional classifier such SVM, which belongs to the segmental classifier based framework. Authors in [20] use DNN for frame-level tone classification using co-articulation features extracted from raw MFCCs as input without pitch tracking. [21] proposed a method that fully automates tone classification of syllables in Mandarin Chinese, which takes as input the raw tone data and uses convolutional neural networks (CNN) to classify the tones using raw MFCC other than manually edited F0 (fundamental frequency).

In NLP research community, RNN is often used to convert an input word sequence into a fixed dimensional vector, such as in the Encoder-Decoder framework in machine translation [16] and distributed sentence representation [22]. For sentence classification task, authors in [18] in proposed to map the entire word sequence into a vector for classification. Concerning the possible heterogeneous inputs (sequential or segmental) of the tone model, it is appealing to convert pitch related sequence into a fixed-dimensional vector and classify into tone types along with other arbitrary segmental input features. Inspired by this, we proposed to use RNN as a tone modeling framework. We convert the frame based pitch-related observation sequence into a fixed dimensional vector and classified into tone types using a softmax layer. We explore to use methods such as feature splicing, mean pooling and full-syllable tone embedding to improve tone classification accuracy. Also, tone embeddings and durations of contextual syllables are utilized to facilitate tone classification. According to the results, we found the Encoder-Classifier tone model based on RNN combines the advantages of both the sequential tone model and segment classification model. The framework is convenient to model long span features, transfer sequential

^{*}This work was supported by the National Science Fundation of China (61365005,61663044).

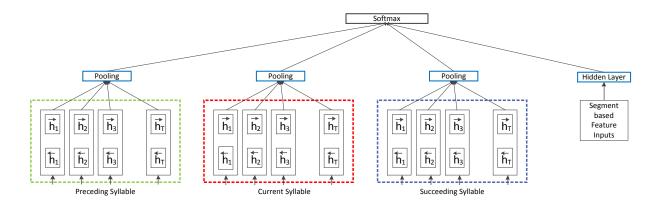


Fig. 1. Tone modeling using RNN encoder-classifier based framework, including an auxiliary input layer

observations to fixed dimensional vector, automate the extraction of tone nuclei of the tones, and easy to incorporate contextual tonal information, hence to combine with other segment based features. We also show a preliminary comparison with the ML and MMI trained GMM-HMM tone models.

The remainder of this paper is organized as follows: In Section 2, the Encoder-Classifier based tone model is described. Section 3 gives the experiments and the results along with various experimental setups. Finally in section 4 the conclusions drawn from the work are given and the future work is presented.

2. RNN ENCODER-CLASSIFIER TONE MODELING

Here, we briefly describe the underlying framework, called RNN Encoder-Classifier. The framework comprises two parts: The first part maps the input observation sequence to a fixed dimensional vector (tone embedding) using the RNN. The second part classifies the tone embedding (or a few tone embeddings of successive syllables) into the five tone labels. The framework enables the network to be trained to discriminate between tones from variable-length speech segments and other manually designed segmental features can be conveniently incorporated as well. The framework is illustrated in Figure 1.

In the Encoder-Classifier framework, an encoder reads the input observation sequence of vectors $\mathbf{x}=(\mathbf{x}_1,\cdots,\mathbf{x}_T)$ and converts them into a compressed vector \mathbf{c} . The most common approach is to use an RNN, which is a neural network that consists of a hidden state \mathbf{h} an output y which operates on the variable length sequence \mathbf{x} . At each time t, the hidden state \mathbf{h}_t of the RNN is update by

$$\mathbf{h}_t = f(\mathbf{x}_t, \mathbf{h}_{t-1}). \tag{1}$$

The compressed vector \mathbf{c} is a function of the output sequence of the hidden states:

$$\mathbf{c} = q(\mathbf{h}_1, \cdots, \mathbf{h}_T). \tag{2}$$

The layer for this purpose is referred to as the pooling layer. f and q are some nonlinear functions. Given the vector \mathbf{c} , the predict layer define a probabilities over the tone labels \mathbf{y} by

$$p(\mathbf{y}|\mathbf{x}) = g(\mathbf{c}),\tag{3}$$

where $\mathbf{y} = (y_1, \dots, y_5)$ represent the five tone labels given \mathbf{x} and q is a nonlinear, potentially multi-layered, function that outputs the

posterior probabilities of y. The two components of the proposed RNN Encoder-Classifier are jointly trained to maximize the conditional log-likelihood

$$\max_{\theta} \frac{1}{N} \log p_{\theta}(\tilde{y}_n | \mathbf{x}_n), \tag{4}$$

where θ is the set of the model parameters and $(\mathbf{x}_n, \tilde{y}_n)$ is the pair from the training set. The more sophisticated network structures that improve the model will be described in the experiments.

3. EXPERIMENTS AND RESULTS

3.1. The database

The proposed method is evaluated on a Mandarin speech recognition database. The '863 project' Mandarin speech database is used, which is a corpus for continuous speech recognition collected for the Chinese National '863 Project'. It has a total of about 110-hour recordings spoken by 160 speakers (80 females and 80 males). The database contains 92,243 utterances. In our experiments, 86,271 utterances are selected as the training set, the rest are used for evaluation. Table 1 lists the two subsets of the database and the distribution of the tones in the corpus.

The pitch related features were extracted by using the compute <code>-and-process-kaldi-pitch-feats</code> command in the Kaldi speech recognition toolkit [23] with default command options. Each input observation vector has 3 dimensions: The log-pitch with Probability of Voicing (POV) weighted mean subtraction, and the time derivative of log-pitch and the warped Normalized Cross Correlation Function (NCCF) [24]. The features are normalized by speaker dependent means and variances. Before training the tone model, we use DNN-HMM based acoustic models trained for speech recognition to obtain phone boundary information for each phone-segment using Viterbi alignment.

3.2. Results

3.2.1. Baseline

For the baseline, the inputs to RNN are only the observations of the final portion of the syllable, which conforms to the common knowledge that tone is perceived mainly in the final part of a syllable. The input observation uses current frame (without feature splicing). As

Table 1. Number of samples of the tones in the speech corpus (K)

Data	Tone0	Tone1	Tone2	Tone3	Tone4	Total
Train	60.4	219.9	234.7	172.5	359.7	1047.3
Test	4.1	15.1	16.2	11.4	24.6	73.4

for the RNN, Elman neural network is used, which keeps track of the previous hidden layer states through its recurrent connections:

$$\mathbf{h}_t = \sigma(\mathbf{W}\mathbf{x}_t + \mathbf{V}\mathbf{h}_{t-1} + \mathbf{b}),\tag{5}$$

where **W** and **V** are the weight matrices and **b** is the bias vector. $\sigma(\cdot)$ is the sigmoid function. The dimension of the input observations **x** is 3. The hidden layer size is set to 250. As for the pooling layer, which combines the sequence of vectors **h** into a single vector **c** that represent the tone, we first experiment with *Last Pooling*, which takes the hidden layer output of the last frame as the tone embedding:

$$\mathbf{c} = \mathbf{h}_T. \tag{6}$$

The output of the pooling layer c is fed into the classifier, for which we use a simple softmax function as g in (3) such that:

$$p(\mathbf{y}|\mathbf{x}) = \text{softmax}(\mathbf{c}). \tag{7}$$

Using the above setups, the baseline tone classification accuracy on the test set is 70.7%.

3.2.2. Feature splicing

Feature splicing has shown to be effective in speech recognition. For GMM-HMM based acoustic model, utilization of spliced features is more complicated and is often achieved by using LDA-MLLT (Linear Discriminant Analysis and Maximum Likelihood Linear Transform [25]) method. In comparison, DNN/RNN based acoustic model splicing the input features is straight-forward to implement. In this setup, each feature vector is extracted from a small overlapping window of observation frames. The input feature of the RNN has a dimension of 27 by concatenating a context of 4 frames left and right of the current frame (9 frames in total). It is shown in Table 2 that feature splicing has greatly improves tone classification performance, which yields 5.3% absolute improvement compare with the baseline using single frame input.

3.2.3. Pooling

In RNN based tone modeling, the hidden layer outputs the dynamic state of the pitch contours. In baseline RNN with last pooling, using the hidden state of the last frame does not fully consider the pitch contour of the entire segment. We tried another two pooling mechanisms: *Average pooling* and *Max pooling*. Average pooling compute tone embedding by averaging all the hidden vectors

$$\mathbf{c} = \mathbf{h}_{avg} = \frac{1}{T} \sum_{t}^{T} \mathbf{h}_{t}, \tag{8}$$

and max pooling takes the element wise maximum of h_t

$$\mathbf{c} = \mathbf{h}_{max}.\tag{9}$$

It is found with average pooling, tone classification accuracy improves by 1.3% absolute over the baseline with spliced input features (76.0%). Max pooling shows a comparable performance (77.4%). We think the last hidden state \mathbf{h}_T can not long span tone information over the whole segment. Utilization of max pooling or average pooling will consider pitch trends in the entire segment.

Table 2. Tone classification accuracy of the RNN based models (%)

Input	Configuration	Train	Test
	Baseline	80.9	70.7
Final	Splicing	83.8	76.0
Observations	Average Pooling	85.9	77.3
	Max Pooling	85.8	77.4
	Average Pooling ①	88.0	79.7
Syllable	Max Pooling	88.3	79.3
Observations	Backward RNN	88.1	80.2
	Bi-directional RNN	88.2	79.4
	① +Preceeding	88.7	80.6
Syllable	① +Succeeding	88.9	80.9
Observations	① +Both	89.7	82.1
	① +Duration	90.4	82.9

3.2.4. Forward, Backward and Bidirectional Variants

The baseline RNN described in (1) and (5) reads the input sequence $\mathbf{x} = (\mathbf{x}_1, \cdots, \mathbf{x}_T)$ in order starting from the first frame \mathbf{x}_1 to the last one \mathbf{x}_T . It is also possible to take into account future information with a single backward pass. A more appealing model would consider both past and future information at the same time. Researchers have propose to use a bidirectional RNN, successfully used recently in speech recognition. It could be interesting to see whether BiRNN is helpful to Encoder-Classifier based tone model.

A BiRNN consists of a forward and a backward RNNs. The forward RNN \overrightarrow{f} reads the input sequence as it is ordered (from \mathbf{x}_1 to the last one \mathbf{x}_T) and calculates a sequence of forward hidden states $(\overrightarrow{\mathbf{h}_1}, \cdots, \overrightarrow{\mathbf{h}_T})$. The backward RNN \overleftarrow{f} reads the sequence in the reverse order (from \mathbf{x}_T to \mathbf{x}_1), resulting in a sequence of backward hidden states $(\overleftarrow{\mathbf{h}_T}, \cdots, \overleftarrow{\mathbf{h}_1})$. In Encoder-Classifier based tone modeling using backward RNN, the tone embedding is the averaged backward hidden states

$$\mathbf{c} = \overleftarrow{\mathbf{h}}_{avg} = \frac{1}{T} \sum_{t}^{T} \overleftarrow{\mathbf{h}_{t}}.$$
 (10)

When BiRNN is used, the tone embedding is computed by concatenating the averaged forward hidden states and the averaged backward hidden states:

$$\mathbf{c} = \overrightarrow{\mathbf{h}}_{avg} \oplus \overleftarrow{\mathbf{h}}_{avg}, \tag{11}$$

where \oplus denotes the concatenation operation. The hidden layer of the backward RNN also has 250 hidden units. It is shown in Table 2 that the backward RNN shows slight better accuracy on the test set, but the Bi-directional RNN shows even slight lower accuracy. We think the tone classification model, which classify the entire model into a class label does not benefit much from the BiRNN. This task is different from traditional sequence labeling task, which uses forward and backward information to help predict current frame label. For segmental classification task, the output of average pooling has to some extent contained the overall contour information for classifying the whole input segment.

3.2.5. Using Full Syllable Tone Embedding

In traditional tone classification task, it is commonly assumed the pitch values exists in the voiced part of a syllable. In the baseline, tone models classification are conducted on features extracted from the final part of a syllable. Here we train the RNN using features

spanning over the whole syllable. It is shown substantial improvement (2.6% absolute) over the result from using only the pitch values extracted from the final portion (77.3%). This indicates that the boundaries obtained by the DNN speech recognizer might be inaccurate or they might not the best for tone classification task. Another reason is that features for tone discrimination do not merely exist in the final part of syllable. As stated in [26], a syllable F0 contour could be divided into three segments: onset course, tone nucleus and offset course. Tone nucleus is a piece of F0 contour that represents pitch targets of the lexical tone, which contains the most critical information for tonality perception. Tone nucleus obtained within the final part of a syllable might be lost. The tone embeddings extracted by RNN using full-syllable observations is capable of detecting the underlying crucial information to discriminate the tones.

3.2.6. Integration of Supra-Segmental Information

As claimed, the superiority of Encoder-Classifier based tone model to the frame-synchronous model (HMM or HCRFs) is its convenience of integrating supplemental segment-based features. To achieve this goal, we extend the model by adding auxiliary inputs which provides complementary information to the input layer. The auxiliary input layer can be used to feed in arbitrary additional information, either automatically learned features or manually designed features.

A. Contextual Tone Embeddings

Tone classification on continuous speech is much more difficult than isolated tone classification task because of the co-articulation effect, that is, tone is not only determined by pitch contour of the current syllable, but also heavily influenced by the behavior of left and right tones. How to characterize tone variation with different contexts has been widely discussed. The context-dependent HMMs [4] were selected by observing the co-articulation effect of neighboring tones were investigated. The decision tree-based clustering method was applied to obtain the optimal context-dependent models [11]. These approaches showed effectiveness in reducing diversity of tone with different contexts; however, they did not really integrate context tone features into either training or recognition.

It is straightforward to model the contextual tone information for segment based models. In [6], overlapped ditone model is proposed which integrates contextual pitch features for GMM based tone models. However, it needs manually designed features. For pure frame based model such HMM or CRFs, modeling the context feature is rather difficult. For example, to utilize the supra-segmental nature of Mandarin tones, we proposed a feature extraction method for HMM based tone modeling in [7]. The method uses linear transforms to project F0 features of neighboring syllables as compensations, and adds them to the original F0 features of the current syllable. The transforms are discriminatively trained by using an minimum Beyesian risk (MBR) objective function. Though the method is successful, still it needs manual time-normalization of the pitch values of preceding syllable and following syllable. The Encoder-Classifier based model makes the use of the supra-segmental features easy to implement. To use the contextual tone features, the input of softmax classifier is

$$\mathbf{c} = \mathbf{h}_{avg}^{prec} \oplus \mathbf{h}_{avg}^{curr} \oplus \mathbf{h}_{avg}^{succ}, \tag{12}$$

where \mathbf{h}_{avg}^{prec} , \mathbf{h}_{avg}^{curr} and \mathbf{h}_{avg}^{succ} are respectively the average hidden vectors of the preceding syllable, the current syllable and the succeeding syllable RNN.

B. Duration

Table 3. Results on GMM-HMM based tone models

Criterion	Train	Test
MLE	71.5	70.4
MMI	76.3	75.7

Utilization of duration as feature has shown to be effective in tone classification. The Encoder-Classifier framework makes it easy to use duration feature along with the sequential input observations. We first normalize the durations (in frames) of each segment by the mean and variance of all the segments. Then the durations of the successive 3 three syllables (current syllable, preceding syllable and succeeding syllable) are used to form a 3-dim duration feature vector d. The duration vector is sent into a sigmoid hidden layer (with the size of 10) and the outputs are concatenated with the tone embeddings of the contiguous three syllable as the total input of the final softmax layer,

$$\mathbf{c} = \mathbf{h}_{avq}^{prec} \oplus \mathbf{h}_{avq}^{curr} \oplus \mathbf{h}_{avq}^{succ} \oplus \sigma(\mathbf{d}). \tag{13}$$

It is shown in Table 2 that combination of the tone embeddings from successive syllables (preceding, succeeding or both) shows better results. Tone classification accuracy using tone embeddings from three successive syllables is improved by 2.4% absolute better than that using tone embedding of only the current syllable (79.7% on the test set). By adding the duration feature, a further slight improvement (0.8%) is obtained. These results indicate the proposed model accommodates both automatically learned feature and arbitrary manually designed features.

3.2.7. GMM-HMM based results

We show a preliminary comparison results with the GMM-HMM based tone model. For GMM-HMM based tone modeling, we trained context-independent GMM-HMMs using ML estimation and the run MMI discriminative training for further improvement. The classification accuracy on the test set is 70.4% for ML trained GMM-HMMs and improves to 75.7% for MMI trained GMM-HMMs. By comparing the results from RNN in Table 2 and those from GMM-HMMs in Table 3, we have seen the superiority of the RNN based tone models to the GMM-HMMs base tone models.

4. CONCLUSION AND FUTURE WORK

We have proposed an Encoder-Classifier tone modeling framework using RNN for Mandarin tone classification task. In the framework, extracted frames of features for tone recognition are fed in to the RNN and casted into a fixed dimensional vector (tone embeddings) and classified into tones using a softmax classifier. We show various method to improve the model. The proposed Encoder-Classifier framework is promising in that it allows both sequence based observations and arbitrarily designed segment based features.

As discussed, the presented framework is at the early stage. Methods can be used to for further improvement of the model, such as context-dependent model and attention mechanism. A comprehensive experimental study needs to be carried out. Thorough comparisons with DNN-HMM based tone model and segment based models (SVM and DNN) should be investigated. End-to-end learning for the tone models without explicit pitch feature extraction could be further explored. Its application to tonal mispronunciation detection task for computer assisted language learning is remained and to be explored.

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