ALMOST-UNSUPERVISED SPEECH RECOGNITION WITH CLOSE-TO-ZERO RESOURCE BASED ON PHONETIC STRUCTURES LEARNED FROM VERY SMALL UNPAIRED SPEECH AND TEXT DATA

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ABSTRACT

Producing a large amount of annotated speech data for training ASR systems remains difficult for more than 95% of languages all over the world which are low-resourced. However, we note human babies start to learn the language by the sounds of a small number of exemplar words without hearing a large amount of data. We initiate some preliminary work in this direction in this paper. Audio Word2Vec is used to obtain embeddings of spoken words which carry phonetic information extracted from the signals. An autoencoder is used to generate embeddings of text words based on the articulatory features for the phoneme sequences. Both sets of embeddings for spoken and text words describe similar phonetic structures among words in their respective latent spaces. A mapping relation from the audio embeddings to text embeddings actually gives the word-level ASR. This can be learned by aligning a small number of spoken words and the corresponding text words in the embedding spaces. In the initial experiments only 200 annotated spoken words and one hour of speech data without annotation gave a word accuracy of 27.5%, which is low but a good starting point.

Index Terms— automatic speech recognition, low resource, semi-supervised

1. INTRODUCTION

Huge success in automatic speech recognition (ASR) has been achieved and widely used in many daily applications. However, with the existing technologies, machines have to learn from a large amount of annotated data to achieve acceptable accuracy, which makes the development of such technology for a new language with very low resource challenging. Collecting a large amount of speech data is expensive, not to mention having the data annotated. This remains true for at least 95% of languages all over the world. Although substantial efforts have been reported on semi-supervised ASR [1 2 4 5 6], in most cases a large amount of speech data including a good portion annotated were still needed. So training ASR systems with very small data, most of which are not annotated, is an important but unsolved problem.

On the other hand, we note human babies start to learn the language by the sounds of a small number of exemplar words without hearing a large amount of data. It is certainly highly desired if machines can do that too. In this paper we initiate some preliminary work in this direction.

Audio Word2Vec has been proposed recently to transform spoken words (signal segments for words without knowing the underlying word it represents) to vectors of fixed dimensionality [7]. These vectors are shown to carry the information about the phonetic structures of the spoken words. Segmental Audio Word2Vec was further proposed to jointly segment an utterance into a sequence of spoken words and transform them into a sequence of vectors [8]. Unsupervised phoneme recognition was then achieved to some extent by making the duration of spoken words shorter and mapping the clusters of vector representations to phonemes even without aligned audio and text [9].

To further achieve word-based speech recognition in a very low resource setting, algorithms similar to the skip-gram model [10] were used to capture the contextual information in speech data and obtain a set of audio semantic embeddings [11 12 13]. A transformation matrix is then learned to align the audio semantic embeddings with the semantic embeddings learned from text, based on which speech recognition can be performed. In this way, two semantic embedding spaces are aligned, and speech recognition is performed. However, semantic information has to be learned from the context out of extremely large amount of data, such as hundreds of hours of speech data [11 13], while rarely used words still have relatively poor embeddings for lack of contextual information. Achieving ASR through the semantic spaces of speech and text seems to be a too far route for the low-resource requirements considered here.

In this work, we discover the phonetic structures among text words and spoken words in their respective embedding spaces with only a small amount of text and speech data without annotation, and then align the text and speech embedding spaces using a very small number of annotated spoken words. The word accuracy achieved in the initial experiments with only 200 annotated spoken words and one hour of audio without annotation is 27.5%, which is still relatively low but a good starting point.

2. PROPOSED APPROACHES

In Sections 2.1 and 2.2 phonetic embeddings of spoken and text words are respectively learned from audio and text data with relatively small size. The two embedding spaces are then aligned with a very small set of annotated spoken words in Section 2.3 so speech recognition can be achieved. In Section 2.4 a very weak language model is used to rescore the recognition results.

2.1. Phonetic Embedding of Spoken Words

We denote the speech corpus as \(X = \{x_i\}_{i=1}^M\), which consists of \(M\) spoken words, each represented as \(x_i = (x_{i1}, x_{i2}, ..., x_{iT})\), where \(x_{it}\) is the acoustic feature vector at time \(t\) and \(T\) is the length of the spoken word. In the initial work here we focus on the alignment of words in speech and text, so we assume all training spoken words have been properly segmented with good boundaries. There exist many approaches which can segment utterances automatically [14].
To model the phonetic structures of text words, we represent each text word with a phoneme sequence, and each phoneme represented as a vector of articulatory features [20]. So the articulatory features of a text word is denoted as $y_i = (y_{i1}, y_{i2}, ..., y_{iL})$, where $y_{ij}$ is the vector for the $i$th phoneme and $L$ is the number of phonemes in the word. Then we feed $y_i$ into an autoencoder for text words ($Enc_t$ and $Dec_t$) to obtain a text embedding $v_t$, as in the right part of Fig. 1. The objective of $Enc_t$ and $Dec_t$ is to reconstruct the original articulatory feature representation.

More specifically, we use 15-dim SPE (The Sound Pattern of English [20]) articulatory features, respectively corresponding to the features sonorant, syllabic, consonantal, high, back, front, low, round, tense, anterior, coronal, voice, continuant, nasal, and strident. A value 1 is assigned to a dimension if a phoneme is positive for the corresponding feature, and a value -1 is assigned if negative. A value 0 is assigned if a phoneme does not have the corresponding feature. For example, a word “house” is represented with a phoneme sequence (HH, AW, S), and the phoneme “S” can be represented with (-1, -1, -1, -1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, -1, 1, -1, 1).

2.3. Alignment of Speech and Text

This approach was inspired from the Mini-Batch Cycle Iterative Closest Point (MBC-ICP) [21]. Since both $Enc_p$ and $Enc_t$ encode the phonetic structures of the words in their respective latent spaces for $v_p$ and $v_t$, we may assume in these latent spaces the relative relationships among words should have similar structures (the phonetic structures). For example, the relationships among the words “other”, “brother” and “bother” should be very similar in the two spaces. Similarly for all other words. It is therefore possible to align the two spaces with a little annotation.

All the vector representations $v_p$ and $v_t$ are denoted as $V_p = \{v_p \}_{i=1}^M$ and $V_t = \{v_t \}_{i=1}^{M'}$, respectively, where $M$ is the number of spoken words in the speech corpus, and $M'$ the number of distinct words in the text corpus. These vectors are first normalized to zero mean and unit variance in all dimensions, and then projected onto their lower dimensional space by PCA. The projected vectors in the principal component spaces are respectively denoted as $A = \{a_i \}_{i=1}^M$ and $B = \{b_i \}_{i=1}^{M'}$. This is shown in the middle part of Fig. 1. Assuming the relative relationships among vectors remain almost unchanged to a good extent after PCA, PCA makes the following alignment easier.

To align the latent spaces for speech and text, we need a small number of “seeds” or paired speech and text words, referred to as the training data here, is denoted as $A' = \{a_n \}_{n=1}^N$ and $B' = \{b_n \}_{n=1}^N$, in which $a_n$ and $b_n$ correspond to the same word. $N$ is a small number, $N \ll M$. Then a pair of transformation matrices, $T_{ab}$ and $T_{ba}$ are learned, where $T_{ab}$ transforms a vector $a$ in $A$ to the space of $B$, that is, $b = T_{ab}a$, while $T_{ba}$ maps a vector $b$ in $B$ to the space of $A$. $T_{ab}$ and $T_{ba}$ are initialized as identity matrices and then learned iteratively with gradient descent minimizing

![Fig. 1. The whole architecture of the proposed approach.](image-url)
the objective function:

\[ L = \sum_{n=1}^{N} \| b_n - T_{ab} a_n \|^2 + \sum_{n=1}^{N} \| a_n - T_{ba} b_n \|^2 \]

\[ + \lambda' \sum_{n=1}^{N} \| a_n - T_{ba} T_{ab} a_n \|^2 \]

\[ + \lambda' \sum_{n=1}^{N} \| b_n - T_{ab} T_{ba} b_n \|^2. \]

In the first two terms, we want the transformation of \( a_n \) by \( T_{ab} \) to be close to \( b_n \) and vice versa. The last two terms are for cycle consistency, i.e., after transforming \( a_n \) to the space of \( B \) by \( T_{ab} \) and then transforming back by \( T_{ba} \), it should end up with the original \( a_n \), and vice versa. \( \lambda' \) is a hyper-parameter.

After we obtain the transformation matrix \( T_{ab} \), it can be directly applied on all phonetic vectors \( v_p \). For each spoken word with phonetic vector \( v_p \), we can get its PCA mapped vector \( a_i \) and the transformed vector \( b_i = T_{ab} a_i \). Then we can find the nearest neighbor vector of \( b_i \) among all vectors in \( B \), whose corresponding text word is the result of alignment, or ASR result.

### 2.4. Rescoring with a Language Model

We can use a language model to perform rescoring as illustrated in Figure 2. During testing, for each spoken word \( a_i \), we obtain a vector \( b_i = T_{ab} a_i \). We find the \( K \) nearest neighbor vectors of \( b_i \), \( \{b_k\}_{k=1}^{K} \), among the vectors in \( B \). Each \( b_k \) corresponds to a text word, with the cosine similarity between \( b_i \) and \( b_k \) (numbers in red in Figure 2) as the score. The language model scores are the numbers in green. Any kind of language modeling can be used here, and the cosine similarities and language model scores are integrated to find the best path in beam search.

### 3. EXPERIMENTS

#### 3.1. Dataset

LibriSpeech [22] for read speech in English derived from audiobooks were used here. It contains 1000 hours of speech uttered by 2484 speakers. We used one-hour speech from the “clean-100” set as the training data for phonetic embedding of spoken words. This training set contains a total of 9022 spoken words for 1533 distinct words. In the initial experiments here we used word boundaries from LibriSpeech, although joint learning of segmentation and spoken word embedding is achievable [8]. 39-dim MFCCs were taken as the acoustic features. The “clean-100” set of 100 hours of speech includes 32219 distinct words. We trained phonetic embedding of text words on all these 32219 words. For the “seeds” or paired data, we selected the \( N \) most frequent text words out of the 9022 in the one-hour training data, and randomly chose a corresponding spoken word from the one-hour set for each text word to form the paired training set, \( A' \) and \( B' \). In this way, each word had at most one example in the paired data. The alignment or ASR results were evaluated on the whole one-hour data set, but excluding those used in the paired data.

#### 3.2. Model Implementation

The phonetic encoder \( Enc_p \), speaker encoder \( Enc_s \) and text encoder \( Enc_t \) were all single-layer Bi-GRUs with hidden layer size 256. The decoders \( Dec_c(p+s) \) and \( Dec_t \) were double-layer GRUs with hidden layer size 512 and 256 respectively. The speaker discriminator \( Dis_s \) was a fully-connected feedforward network with 2 hidden layers of size 256. The value of threshold \( \lambda \) for the constraint of \( v_s \) in Section 2.1 was set to 0.01. \( \lambda' \) in Equation (1) of Section 2.3 was set to 0.5. In all training processes, the initial learning rate was 0.0001 and the mini-batch size was 64.

#### 3.3. Visualization of PCA Vectors

We visualized several typical examples of vectors \( v_p \) and \( v_t \) in the subspaces of the first three PCA components. For cleaner visualization, we only show the averages of the vectors corresponding to all spoken words for the same text word. In Fig. 3(a) and (b) respectively for \( v_p \) and \( v_t \), we show the six vectors corresponding to the six words \{time, eye, other, times, eyes, others\}. We see the triangle structures for the three words and the difference vectors between
Table 2. The results of beam search with different beam widths.

| Beam width | Top-1 acc. (%) |
|------------|----------------|
| no language model | 17.2 |
| 1 | 21.5 |
| 3 | 24.9 |
| 10 | 26.4 |
| 50 | 27.5 |

Table 3. Examples of beam search with beam width K=50.

| (1) | before | ... ned if feet mather flowers out all ... |
|     | after  | ... and if she gathered flowers out all ... |
|     | reference | ... and if she gathered flowers at all ... |
| (2) | before | ... cur mother whiff shrill in zee her ... |
|     | after  | ... her mother was three in the her ... |
|     | reference | ... her mother was three in teaching her ... |
| (3) | before | ... key beganne to pearl her hair ... |
|     | after  | ... she began to tell her head ... |
|     | reference | ... she began to curl her hair ... |

The beam width for beam search ranged from 1 to 50. We simply summed the cosine similarities and the language model scores with weights 1 and 0.05 during the rescoring. The results are listed in Table 2. We see the very weak language model offered very good improvements (27.5% vs 17.2% for K = 50), verifying the mapping from spoken to text words performed the word-level recognition to a certain extent. Some examples showing how the beam search helped (beam width K = 50) in Table 3. We see the language model may correct some phonetically similar but semantically different words. It is believed with a stronger language model and a well-designed fusion approach, the accuracy can be further improved.

3.4. Ablation Studies

Here we further verify that the disentanglement of speaker characteristics for $V_p$ and the SPE-based representation used in text word embedding both improved the performance in Table 4 (N = 200 without language model). Removing the disentanglement and/or representing the phonemes with one-hot vectors instead of SPE-based features led to some performance degradation.

4. CONCLUSION

In this work, we let the machines learn the phonetic structures among spoken and text words based on their embeddings, and learn the mapping from spoken words to text words based on the transformation between the two phonetic structures using a small number of annotated words. Initial experiments with only one hour of speech data and 200 annotated spoken words gave an accuracy of 27.5%. There is still a long way to go, and a very wide space to be explored.

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