A Statistical Model for an Automatic Procedure to Compress a Word Transcription Dictionary

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Abstract

Various experiments have conclusively shown that superior continuous speech recognition performance is obtained when using context-dependent phonemic models. However, we have observed that using an explicit context-dependent phonemic model can yield many transcriptions for a single lexicon entry. In this work, we study the compression of the word transcription dictionaries (WTD) into a more compact form to balance the need between flexibility and reliability. Based on a measure of a likelihood function, a statistical model for an automatic procedure to compress a WTD is developed. The compressed dictionary is then used for sentence recognition in a continuous speech recognition system. Experimental results indicate a substantial improvement of the recognition rate after compression.

1 Introduction

Several continuous speech recognition systems currently being developed use context-dependent models which seek to capture the pronunciation variations resulting from phonetic context effects. It has been observed that with these models, large vocabulary speech recognition systems usually necessitates to compress, from some standard references, a word phonetic transcription dictionary (WTD) [1, 2, 3, 4]. Such a dictionary generally gives a single transcription for a lexicon entry. Continuous speech recognition systems have shown satisfactory results when using dictionaries prepared in this way [3, 5, 6, 7]. However, because of the large variations in the pronunciation of a given word [8, 9, 10, 11, 12, 13,], it is very difficult, when compressing a dictionary, to capture its most representative variant. Word transcriptions are first obtained from the context-dependent phonemic model CODEPHON-STM based on the automatically expending speed and context (AESC) approach developed in our laboratory [11, 4], and then compressed into a more compact form to balance the need between flexibility and reliability using an automatic procedure. In fact, the direct word transcriptions given by CODEPHON-STM can yield many transcriptions for a single lexicon entry.

The different transcriptions of a word could reflect differences in dialect, phonetic contexts and speaking rates [11]. As it is well known, too many variations in transcribing words can also lead to an increased word confusions. In this paper, we describe a method to compress a multiple word transcription dictionary which gives good results. The method is based on a statistical modelling of the speech, and selects the transcriptions that maximise some likelihood function. The compressed dictionary is then used for sentence recognition in ML-VINICS [14, 6, 15, 16], our multi-lingual phoneme-based continuous speech recognizer. On a task of an 1070 word vocabulary and a test set grammar perplexity of 20, the system achieves a word accuracy of 94.9%, for a normal speed, which represents an error reduction of about 72% compared to the recognition results when using a standard dictionary.

This paper is organized into five sections. For providing back-ground material, the AESC approach and the phonemic model are briefly described in section 2. In section 3, the algorithm for compressing the word transcription dictionaries is described. Experimental results on the AGIMMO database using the ML-VINICS system are provided in section 4. Section 5 contains a conclusion.

2 Preparing a WTD Using the AESC Approach

2.1 The AESC Approach

The AESC purpose is to deduce context and speed dependent rules (CSDR) rules from a large labeled continuous speech corpus in order to construct a mapping between the symbolic phonemes in the WTD and their real pronunciations from the labeled data-base [4, 9, 11, 17, 18, 14]. The AESC approach goes through the following steps:

- Step-1: training of the phonemic model
 1. Labelling of a large continuous speech corpus
 2. Segmentation of this speech corpus
 3. Determination of its triplets
 4. Identification of the phonemes in the middle of each triplet
- 5. Generation of the context and speed dependent rules (CSDR)
- Step-2: preparing the new WTD
 1. Computation of the speaking rate
 2. Loading of the CSDR corresponding to this speed
 3. Transformation of the sequence in the WTD of ML-VINICS with the loaded CSDR
 4. Generation of the new WTD

2.2 The CODEPHON-STM Model

In this section we briefly examine a context-dependent phonemic model which uses a statistical method to generate the CDSRs. Further details are given in [4].

To model the contextual and speaking rate influence, we propose a stochastic trajectory model. A speech signal representing a symbol can be represented, in a parametric space, as a point which moves as articulatory configuration changes [19, 20, 21]. The trace of this moving point is called the trajectory of the symbol. Several techniques were applied to model these trajectories [22, 23, 24, 25].

Let us consider a sequence of parameter vectors: $\mathbf{v}_0, \mathbf{v}_1, \dots, \mathbf{v}_t, \dots, \mathbf{v}_T$, where T is the total number of vectors in a given utterance. Each point $\mathbf{v}_t \in \mathbb{R}^D$ is a D -dimensional vector in some parameter space. Let $\mathbf{V}_t$ be a subsequence of L vectors centered at time slot t :

$$\mathbf{V}_t \triangleq \mathbf{v}_{t-\frac{L}{2}}, \mathbf{v}_{t-\frac{L}{2}+1}, \dots, \mathbf{v}_t, \dots, \mathbf{v}_{t-\frac{L}{2}+L-1} \quad (1)$$

Let $\mathcal{PH} \triangleq \{ph_1, ph_2, \dots, ph_M\}$ be a set of M symbols representing phonemes. In our formulation, it is assumed that to each phoneme symbol are associated N stochastic generators of trajectories, $T_1, T_2, \dots, T_N$. Let $pf(\mathbf{V}_t, T_n, d, ph)$ be the joint probability density function (pdf) of vector sequence $\mathbf{V}_t$, trajectory source T_n , duration d and phoneme symbol $ph \in \mathcal{PH}$.

$$pf(\mathbf{V}_t, T_n, d, ph) = pf(\mathbf{V}_t|T_n, d, ph)P(T_n|d, ph)P(d|ph)P(ph) \quad (2)$$

where

- $pf(\mathbf{V}_t|T_n, d, ph)$ is the pdf of $\mathbf{V}_t$ given T_n , d and ph ,
- $P(T_n|d, ph)$ the probability of T_n given d , and ph ,
- $P(d|ph)$ the probability of d given ph , and
- $P(ph)$ the *a priori* probability of ph .

We use pf for continuous probability density functions and P for discrete probabilities. The marginal pdf $pf(\mathbf{V}_t, ph)$ can be obtained by summing up $pf(\mathbf{V}_t, T_n, d, ph)$ over all trajectories T_n and all durations d :

$$pf(\mathbf{V}_t, ph) = P(ph) \sum_d \sum_{n=1}^N pf(\mathbf{V}_t|T_n, d, ph)P(T_n|d, ph)P(d|ph) \quad (3)$$

The probability of phoneme ph given observation $\mathbf{V}_t$ is therefore:

$$P(ph|\mathbf{V}_t) = \frac{pf(\mathbf{V}_t, ph)}{pf(\mathbf{V}_t)} = \frac{P(ph)}{pf(\mathbf{V}_t)} \sum_d pf(\mathbf{V}_t|d, ph)P(d|ph) \quad (4)$$

where $pf(\mathbf{V}_t|d, ph)$ is the pdf of $\mathbf{V}_t$ given d and ph :

$$pf(\mathbf{V}_t|d, ph) \triangleq \sum_{n=1}^N pf(\mathbf{V}_t|T_n, d, ph)P(T_n|d, ph) = \sum_{n=1}^N pf(\mathbf{V}_t|T_n, d, ph)P(T_n|ph) \quad (5)$$

where we assume that for a given phoneme, the probability of a trajectory source T_n does not depend on durations:

$$P(T_n|d, ph) = P(T_n|ph) \quad (6)$$

The duration probability of each phoneme symbol $P(d|ph)$ is modeled by a Γ -distribution. The plausibility of phoneme is defined by Eq-4. Since $pf(\mathbf{V}_t)$ in this equation does not depend on ph , for our propose of phoneme recognition, i.e. finding the best ph , it is a constant and will be discarded. Also, $\sum_d$ in Eq-4 is changed to $\max_d$. Based on Eq-4 we define the plausibility of symbol ph at time slot t , $\mu_{t,ph}$, as the logarithmic pdf of ph given observation sequence $\mathbf{V}_t$:

$$\mu_{t,ph} \triangleq \log P(ph|\mathbf{V}_t) = \log \left[P(ph) \max_d \{pf(\mathbf{V}_t|d, ph)P(d|ph)\} \right] \quad (7)$$

$$0 \leq t < T, ph \in \mathcal{PH}.$$

After carrying out this step for all the triplets, we get a set of rules for which the condition parts represent the possible triplets of the data base and the production parts represent the phoneme corresponding to the computed $\mu_{t,ph}$. For each speed, we call this set of rules CSR. Using CSR, we change the WTD [15] of ML-VINICS. As a result, we obtain, for each word in the lexicon, an important number of transcriptions. An automatic procedure is developed to compress the dictionary. The procedure is repeated for all the words in the recognition vocabulary. This newly obtained WTD is used to test the ML-VINICS system. The details of this compression procedure are given in the sequel.

3 Dictionary Compression

3.1 Problem Formulation

From sampled speech signal of an utterance, cepstral parameters are computed with 32ms Hamming window each 10ms, resulting in a sequence of N parameter vectors. Let W be the number of words in the lexicon and K the number of phonetic transcriptions of each word. Let $\mathcal{L} \triangleq \{p_1, p_2, \dots, p_L\}$ be the set of L phonetic symbols. We assume that a phonetic transcription of a word is a sequence of phonetic symbols s_n :

$$T \triangleq [s_0, s_1, \dots, s_n, \dots, s_{S(T)}], \forall n, s_n \in \mathcal{L} \quad (8)$$

In the same manner we suppose that a word m belonging to the lexicon may have several phonetic transcriptions:

$$\alpha(m) \triangleq \{T_1, \dots, T_k, \dots, T_{K(m)}\} \quad (9)$$

We denote by $\mu_{i,s}$ the likelihood of an utterance at time slot i , given the phonetic symbol $s \in \mathcal{L}$. $\mu_{i,s}$ can be computed with any adequate method, for example stochastic trajectory models [4]. The duration of a phone is considered as a random variable denoted ρ and the probability for phone s_n with duration $\rho = d$ is denoted $P(d|s_n)$. Let t_n be the time index corresponding to the beginning of the sequence of vectors composing symbol s_n . We introduce the

cumulative likelihood of s_n as being the product of the likelihoods from t_n to $t_{n+1} - 1$, weighted by the duration probability:

$$Q(s_n) \triangleq P(t_{n+1} - t_n | s_n)^\varepsilon \prod_{t_n \leq i < t_{n+1}} \mu_{i, s_n} \quad (10)$$

where $\varepsilon \geq 0$ is a constant. We then introduce the cumulative likelihood of a transcription, i.e., a sequence of phonetic symbols:

$$\phi(T | t_0, t_1, t_2, \dots, t_{S(T)}) = \frac{1}{N} \prod_{s \in T} Q(s) \quad (11)$$

with $t_0 = 0, t_n < t_{n+1}$, and $t_{S(T)} = N - 1$, where N is the total number of vectors in the utterance. Therefore, this plausibility is a function of $t_n, \forall n \in [0, S(T) - 1]$. By optimising the t_n , the value of $\phi(T)$ can be maximised in the following manner:

$$\Phi(T) \triangleq \max_{t_1, \dots, t_{S(T)}} \phi(T | t_1, \dots, t_{S(T)}) \quad (12)$$

For a given word m , the application of equation 12 to each of its transcriptions $T_k \in \alpha(m)$ results in a particular value $\Phi(T_k)$. We denote by $\text{argmax}_{T \in \mathcal{T}} (\Phi(T), j)$ the function that returns the transcription that gives the j^{th} largest value of Φ given the transcription set $\mathcal{T}$. The optimum subset of M transcriptions of the word m is then given by:

$$\hat{\alpha}(m) \triangleq [\hat{T}_1, \hat{T}_2, \dots, \hat{T}_M]_m \quad (13)$$

Where

$$\hat{T}_j \triangleq \text{argmax}_{T \in \alpha(m)} (\Phi(T), j) \quad (14)$$

Only these M -best transcriptions are kept in the sequel at the level of recognition. All other transcriptions are discarded.

3.2 Implementation

Direct application of equation 14 requires precise specification of the beginning and ending positions of a word in the training utterance, which may change as a function of the transcriptions and thus cannot be determined reliably. To avoid such a specification, we need to generate phonetic transcriptions at the utterance level. For a given word m , the generator performs three steps:

- An utterance baseline transcription using a single transcription word dictionary is built by simply concatenating the transcriptions of the words composing an utterance.
- The transcription of the word m is replaced by each of the $K(m)$ transcriptions, yielding $K(m)$ utterance transcriptions where transcriptions for words other than m remain unchanged.
- These utterance transcriptions are used by equation 14 to find out the M -best transcriptions of the word.

The procedure is repeated for all words in the recognition vocabulary.

4 Experiments

We used, for the training step of the phonemic model (step-1), a first labeled corpus (*corpus-1*) consisting of 1780 sentences pronounced three times (with different speeds) by a male speaker. For the continuous speech recognition, we have collected from a regional newspaper a text corpus (AGIMMO) consisting of real estate advertisements. The recognition task of the corpus is described by a grammar [15] of 11030 rules with a vocabulary of 1070 words and a bigram perplexity of 20. The grammar was compiled with our phonetic model CODEPHON-STM into a non-deterministic automaton of about 903619 states, in which transition labels are phoneme symbols. The speech database consists of 1200 sentences pronounced by eight male and two female French speakers. Each speaker read 300 sentences from the corpus. 140 sentences per speaker were used to train the acoustic models of the recognition system, and the remaining 160 were used for testing. Before compression, the CODEPHON-STM model using the AESC approach generated for each word an average of 30 phonetic transcriptions. The compression produced the 2-best transcriptions for each word ($M = 2$).

SPEAKER	SPEED-1 (NORMAL)			SPEED-2 (LOW)			SPEED-3 (HIGH)		
	S	E(30)	C(2)	S	E(30)	C(2)	S	E(30)	C(2)
brs (F)	75.3	87.8	92.3	76.9	88.1	87.8	76.3	87.2	88.8
crm	75.8	88.1	92.8	68.8	84.1	88.1	67.5	78.6	84.4
jel	61.4	76.5	88.7	55.0	72.8	76.5	54.1	70.8	76.7
lar	93.1	95.6	97.8	83.1	92.8	95.6	82.7	90.1	94.0
ols	93.2	98.0	98.9	85.0	92.5	98.0	83.1	93.8	98.4
sat	75.8	85.9	96.1	75.0	86.4	85.9	62.5	81.0	86.1
std	86.3	89.2	93.9	79.4	92.5	89.2	74.4	88.0	92.8
syc (F)	71.8	81.9	89.9	68.1	81.0	82.0	71.9	84.3	81.0
vil	88.7	93.8	98.4	81.9	89.5	93.8	81.9	89.5	90.4
yig	92.5	94.5	98.5	85.6	95.7	94.5	85.6	95.7	93.4
AVERAGE	81.4	89.2	94.9	75.9	87.6	89.2	74.0	86.0	88.6

Table 1: Word recognition for standard (S), extended (E) and compressed (C) dictionaries for different speeds. The figures in parentheses show the number of transcriptions per word used.

In table 1, we report the word recognition rates for the standard single transcription dictionary, the extended dictionary and the compressed dictionary for different speeds. From this table, we see that by using the extended transcription dictionary instead of the single transcription one, the recognition is improved substantially for every speakers. On the average, the recognition percentage increased from 81.4% to 89.2%, yielding an error rate reduction of about 50%. The compression improved consistently the recognition percentage for all speakers and further reduced the remaining error by about 22%. It is worth noticing that the complexity of the recognition task increases exponentially with the num-

ber of transcriptions per word. Therefore in reducing the average transcription number from 30 to 2, we saved in computation time and gained a significant memory space.

5 Conclusion

In this paper we have investigated the use of a method for preparing a WTD in the hope of obtaining a better decoding accuracy than with word transcriptions in the forms of isolated utterances. WTDs are first obtained from a context-dependent phonemic model based on the AESC approach, and then compressed using a statistical cost measure of some likelihood function. Both the compressed, the extended and the standard dictionary are used in evaluating the decoding performance of an automatic continuous speech recognition system. Experimental results indicate a substantial improvement of the recognition rate after compression. Moreover, the compression procedure seems to be capable of capturing the most representative pronunciations from among many variations. In the other hand, since the between-word context dependence has not been incorporated into the context-dependent phonemic model at this stage of decoding, the advantage of using multiple transcriptions might not have been fully utilized.

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