

NON-LINEAR PROBABILITY ESTIMATION METHOD USED IN HMM FOR MODELING FRAME CORRELATION

Qing Guo, Fang Zheng, Jian Wu, and Wenhui Wu

Speech Lab., Dept. of Computer Science and Technology, Tsinghua Univ., Beijing, 100084, P.R.China

ABSTRACT

In this paper we present a novel method to incorporate temporal correlation into a speech recognition system based on HMM. An obvious way to incorporate temporal correlation is to condition the probability of the current observation on the current state as well as on the previous observation and the previous state. But use this method directly must lead to unreliable parameter estimates for the number of parameters to be estimated may increase too excessively to limited train data. In this paper, we approximate the joint conditional PD by non-linear estimation method. The HMM incorporated temporal correlation by non-linear estimation method, which we called it FC HMM does not need any additional parameters and it only brings a little additional computing quantity. The results in the experiment show that the top 1 recognition rate of FC HMM has been raised by 6 percent compared to the traditional HMM method.

1. INTRODUCTION

Hidden Markov modeling (HMM) techniques have been used successfully for speech recognition in the last ten years due to their ease of implementation and modeling flexibility. The success or failure of a HMM system relies on how well the models can characterize the nature of real speech. The underlying assumption in this scheme is that speech is quasi-stationary and these stationary parts can be represented by a single state of a HMM. In the traditional HMM algorithms the probability of duration of a state decreases exponentially with time which is not appropriate for representing the temporal structure of speech. With this in mind, a number of attempts have been made to incorporate some additional knowledge into the traditional HMM scheme [1]-[2]. Typical methods of them are incorporating duration information, the inclusion of higher-order feature sets and the use of correlation among neighboring outputs, etc.

Various approaches have been tried to take account of frame correlation for more realistic modeling. M.Ostendorf et al. [3] propose Stochastic Segment Model, which consists of 1) a time warping of the variable-length segment X into a fixed-length segment Y , and 2) a joint density function of the parameters of the resample segment Y (Gaussian density). They think the segment model represents spectral/temporal structure over the entire phoneme. Similarly, V.Digalakis et al. [4] propose Dynamical System Model. All the two methods tries to directly express speech feature trajectories. While they seem to be successful in extracting dynamic cues for speech recognition under a suitable trajectory assumption, they are not based on widely available HMM technology.

In the case of continuous HMM's, a Gaussian probability density function (PDF) assumption is made between adjacent feature vectors in C.J.Wellekens[5]. In P.Kenny[6], a linear prediction technique is used to parameterize frame correlation.

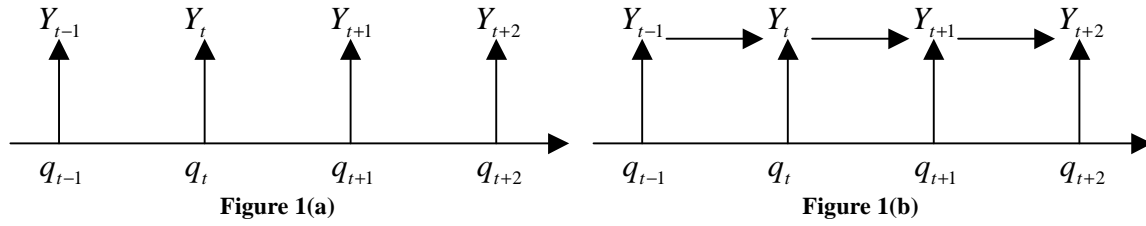
Paliwal [7] incorporated temporal correlation into discrete HMM's by conditioning the probability of the current observation on the current state as well as on the previous observation. With this approach, an output probability distribution (PD) is constructed for each possible pair of state and observation symbols. In their model, $b_{j|X_{t-1}}(X_t) = P(X_t | X_{t-1}, q'_j, \lambda)$ is used to replace $b_j(X_t) = P(X_t | q'_j, \lambda)$ of traditional HMM. The number of parameters in this model to be estimated may increase too excessively to get reliable estimation for the output PD's. S.Takahashi [8][9] propose a bigram-constrained (BC) HMM which has solved this problem. The probability of the current observation in BC HMM depends on the current state as well as on the previous observation too. But a BC HMM is obtained by combining a VQ-code bigram and the traditional HMM. So the number of parameters to be estimated in BC HMM is less than the number of the full parameterization method proposed by Paliwal. A remarkable point of BC HMM is that it has provided a method to combine the joint conditional PD by two separate conditional PD. N.S.Kim [10] propose an algorithm based on Extended Logarithmic Pool which can estimate the joint conditional PD more precisely.

2. MODELING FRAME CORRELATION

In traditional HMM (we only discuss first order left-to-right Markov model), we think the probability of the current observation only depends on the current state, while it doesn't depend on the previous state and the

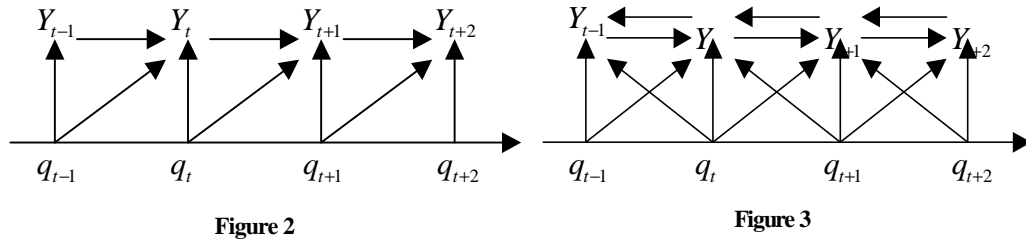
previous observation. The topology of traditional HMM is shown in figure 1(a). In this model the probability of the observation vector Y_t given that the current state is q_t is represented as $P(Y_t | q_t, \lambda)$ which is characterized by $b_{q_t}(Y_t)$.

In BC HMM proposed by S.Takahashi think the probability of the current observation not only depends on the current state but also depends on the previous observation which is shown in figure 1(b). It means that the probability of the observation vector Y_t given that the current state is q_t is represented as $P(Y_t | Y_{t-1}, q_t, \lambda)$ which is characterized by $b_{q_t, Y_{t-1}}(Y_t)$. To actualize the estimation of parameters of the model and the reliability of parameters estimation, BC HMM only need to characterize $P(Y_t | Y_{t-1})$ and $b_{q_t}(Y_t)$. Then $b_{q_t, Y_{t-1}}(Y_t)$ is computed by combining them. At last $b_{q_t}(Y_t)$ is replaced by $b_{q_t, Y_{t-1}}(Y_t)$ which is used for speech recognition. So BC HMM can avoid the problem caused by the full parameterization of Paliwal.



However, the topology shown in figure 2 seems can reflect frame correlation more precisely which means that the probability of the current observation not only depends on the current state but also depends on the previous state and the previous observation. Then the probability of the observation vector Y_t given that the current state is q_t is represented as $P(Y_t | Y_{t-1}, q_{t-1}, q_t, \lambda)$ which is characterized by $b_{q_{t-1}Y_{t-1}q_t}(Y_t)$ (q_{t-1} is the state in $t-1$). The same as the model of Paliwal that using limited train data to full parameterize this model is nearly impossible. So we need to find an approximate arithmetic to compute $b_{q_{t-1}Y_{t-1}q_t}(Y_t)$.

Further, we can adopt the first-order forward and backward frame correlation model shown in figure 3. Then the probability of the observation vector Y_t given that the current state is q_t is represented as $P(Y_t | Y_{t-1}, Y_{t+1}, q_t, q_{t-1}, q_{t+1}, \lambda)$ which is characterized by $b_{q_{t-1}Y_{t-1}q_tY_{t+1}q_{t+1}}(Y_t)$.



Now we discuss how to estimate $p(Y_t | Y_{t-1}, q_t, q_{t-1}, \lambda)$ using non-linear formula.

$$\begin{aligned}
 p(Y_t | Y_{t-1}, q_t, q_{t-1}, \lambda) &= \frac{p(Y_t, Y_{t-1}, q_t, q_{t-1} | \lambda)}{p(Y_{t-1}, q_t, q_{t-1} | \lambda)} \\
 &= \frac{p(Y_t | q_t, \lambda) p(q_t | \lambda) p(Y_{t-1}, q_{t-1} | Y_t, q_t, \lambda)}{p(Y_{t-1}, q_{t-1} | q_t, \lambda) p(q_t | \lambda)} \\
 &= \frac{p(Y_{t-1}, q_{t-1} | Y_t, q_t, \lambda)}{p(Y_{t-1}, q_{t-1} | q_t, \lambda)} p(Y_t | q_t, \lambda)
 \end{aligned} \tag{1}$$

$$\text{Let } f(Y_{t-1}, Y_t, q_{t-1}, q_t, \lambda) = \frac{p(Y_{t-1}, q_{t-1} | Y_t, q_t, \lambda)}{p(Y_{t-1}, q_{t-1} | q_t, \lambda)} \tag{2}$$

$$\text{Then: } p(Y_t | Y_{t-1}, q_t, q_{t-1}, \lambda) = f(Y_{t-1}, Y_t, q_{t-1}, q_t, \lambda) p(Y_t | q_t, \lambda) \tag{3}$$

Further, we approximate $p(Y_{t-1}, q_{t-1} | q_t, \lambda)$ of right term of (2) by $p(Y_{t-1}, q_{t-1} | \lambda)$. We can get:

$$f(Y_{t-1}, Y_t, q_{t-1}, q_t, \lambda) \approx \frac{p(Y_{t-1}, q_{t-1} | Y_t, q_t, \lambda)}{p(Y_{t-1}, q_{t-1} | \lambda)} \quad (4)$$

Then, we use a non-linear estimation formula to compute the right term of the above formula, i.e.:

$$\frac{p(Y_{t-1}, q_{t-1} | Y_t, q_t, \lambda)}{p(Y_{t-1}, q_{t-1} | \lambda)} \approx h(b_{q_{t-1}}(Y_{t-1}), b_{q_t}(Y_t)) \quad (5)$$

At last, we obtain the non-linear estimation formula of $p(Y_t | Y_{t-1}, q_t, q_{t-1}, \lambda)$:

$$\begin{aligned} p^*(Y_t | Y_{t-1}, q_t, q_{t-1}, \lambda) &= f(Y_{t-1}, Y_t, q_{t-1}, q_t, \lambda) p(Y_t | q_t, \lambda) \\ &\approx h(b_{q_{t-1}}(Y_{t-1}), b_{q_t}(Y_t)) p(Y_t | q_t, \lambda) \end{aligned} \quad (6)$$

3. FRAME CORRELATION (FC) HMM

In this section, we use the concept of non-linear estimation to incorporate the correlation of neighboring frames into the traditional HMM. For simplicity, we only take the case of first-order forward frame correlation, which means that the current observation symbol relates only with the observation and the state on the immediate previous frame as figure 2 shows.

FC HMM $\lambda = (N, \pi, A, B, FC)$ which incorporate frame correlation can be defined as follows:

1) N , the number of states in the model;

2) $\pi = \{\pi_i\}$, where $\pi_i = P[q_1 = i], 1 \leq i \leq N$ is the initial probability of the model being in state i , and they satisfy the constraint $\sum_{i=1}^N \pi_i = 1$.

3) $A = \{a_{ij}\}, 1 \leq i, j \leq N$, $a_{ij} = P[q_{t+1} = j | q_t = i]$

4) $B = b_i(O)$ is the probability density function (pdf) for the observation O given that the state is i .

In our system we adopt a state observation density, $b_i(O)$, of the form, $b_i(O) = \sum_{m=1}^M c_{mi} N[O, \mu_{mi}, U_{mi}]$

i.e., a continuous mixture density where O is the observation vector (e.g., cepstral coefficient vector resulting from the LPC analysis), c_{mi} is the mixture weight for the m th component in state i , μ_{mi} is the mean vector for mixture m in state i , and U_{mi} is the covariance matrix for mixture m in state i .

5) The frame correlation PD, $FC = \{f(Y_{t-1}, Y_t, q_{t-1}, q_t)\}$, in which:

We approximate $f(Y_{t-1}, Y_t, q_{t-1}, q_t)$ by a non-linear estimation formula $h(b_{q_{t-1}}(Y_{t-1}), b_{q_t}(Y_t))$.

In FC HMM, $P[O_1 O_2 \cdots O_T | \lambda]$ can be computed as follows:

$$\begin{aligned} P[O_1 O_2 \cdots O_T | \lambda] &= \sum_{\psi=(q_1, q_2, \dots, q_T)} P[O_1 O_2 \cdots O_T, \psi | \lambda] \\ &= \sum_{\psi} [P(\psi | \lambda) P(O_1 O_2 \cdots O_T, \psi | \lambda)] \\ &= \sum_{\psi} \left[P(\psi | \lambda) \prod_{t=1}^T p^*(O_t | O_{t-1}, q_{t-1}, q_t, \lambda) \right] \\ &= \sum_{\psi} \left[P(\psi | \lambda) \prod_{t=1}^T f(O_t, O_{t-1}, q_{t-1}, q_t) b_{q_t}(O_t) \right] \\ &\approx \sum_{\psi} \left[P(\psi | \lambda) \prod_{t=1}^T h(b_{q_{t-1}}(O_{t-1}), b_{q_t}(O_t)) b_{q_t}(O_t) \right] \end{aligned} \quad (7)$$

While using the forward-backward formula to reestimate parameters, $\alpha_t(j)$ and $\beta_t(j)$ are modified as follows:

$$\begin{aligned}\alpha_t(j) &= \sum_{i=1}^N \alpha_{t-1}(i) a_{ij} h(b_i(O_{t-1}), b_j(O_t)) b_j(O_t) \\ &= \sum_{i=1}^N \alpha_{t-1}(i) a_{ij} b_{i|O_{t-1}j}(O_t)\end{aligned}\quad (8)$$

$$\begin{aligned}\beta_t(j) &= \sum_{i=1}^N \beta_{t+1}(i) a_{ji} h(b_j(O_t), b_i(O_{t+1})) b_i(O_{t+1}) \\ &= \sum_{i=1}^N \beta_{t+1}(i) a_{ji} b_{j|O_{t+1}i}(O_{t+1})\end{aligned}\quad (9)$$

Considering the principle that using mixture Gaussian density can approach any PD, we think that the reestimated matrix B characterize the probability density function incorporated frame correlation, i.e. $p(Y_t | Y_{t-1}, q_t, q_{t-1}, \lambda)$.

4. COMPLEXITY ANALYZING

In this section, we analyze the computing complexity and memory complexity of FC HMM incorporated frame correlation by non-linear estimation. Obviously, the model exploits the principle of that using mixture Gaussian density can approach any PD, so $p^*(Y_t | Y_{t-1}, q_{t-1}, q_t, \lambda)$ can be characterized by the weighted sum of M normal distribution. As a result, the model does not bring any memory complexity.

Whenever the training of the model or the recognizing of the model, FC HMM only need to compute $f(Y_{t-1}, Y_t, q_{t-1}, q_t)$ additionally. While the non-linear estimation formula $h(b_j(Y_{t-1}), b_{q_t}(Y_t))$ is used to approximate $f(Y_{t-1}, Y_t, q_{t-1}, q_t)$, only very limited addition and multiplication is added so FC HMM only needs a little more computing complexity than the traditional HMM.

In the model proposed by Paliwal the number of the parameters of B matrix is up to M^2N which is M times than that of the traditional HMM. BC HMM needs to compute $p(Y_t | Y_{t-1})$ in the training of the model so it needs to estimate M^2T parameters additionally. In addition, when recognizing BC HMM needs to compute $p(Y_t | Y_{t-1})$ additionally and especially it needs adjusting the weights of mixture Gaussian density so the computing complexity of speech recognizing is augmented greatly.

5. THE EXPERIMENT RESULT

5.1. Speech Database and Features

The speech database used in experiment is “863 assessment” male speech database. The database consists of 1560 sentences which is parted to three groups as A, B and C. The number of sentences of each group is nearly equal. 38 male each utters one part of sentences. The entire database is parted to the training set, the testing set 1 and the testing set 2. The Testing-Set 1 is the utterance of untrained-speaker. The Testing-Set 2 is the untrained-utterance of trained-speaker.

In experiment, we adopt a five state first order left-to-right Markov model. The output probability of observations in each state is characterized by 5-mixture Gaussian density. 16-dimension cepstral coefficients derived by LPC analysis are used as features of each frame.

5.2. The effect of using non-linear estimation formula in Viterbi-decoding phase

At first, we use the non-linear estimation formula to incorporate frame correlation in Viterbi-decoding and we think which can take advantage of frame correlation to adjust the decoding path and the probability of the path. The recognition result is shown in table 1, from which we can find that the top 1 recognition rate of HMM+FC-Viterbi is 2 percent higher than that of HMM (Viterbi). Moreover, figure 4 shows the $\prod_{t=2}^T f(Y_t | Y_{t-1}, q_{t-1}, \lambda)$ ranking of the correct syllable in all syllables (the data is gained in Testing-Set 1 and Testing-Set 2). The horizontal axis represents the $\prod_{t=2}^T f(Y_t | Y_{t-1}, q_{t-1}, \lambda)$ ranking of the correct syllable in all syllables and the vertical axis represents the percentage of each ranking. From figure 4, we can see that the non-linear estimation formula of frame correlation is helpful to correct recognition of syllables.

Model	Recognition Set	Top 1	Top 2	Top 5	Top 10
HMM +	Training-Set	59.93	76.29	90.12	95.05
	Testing-Set 1	32.50	48.29	70.05	82.98
	Viterbi Testing-Set 2	41.22	58.96	80.47	89.88
HMM +FC- Viterbi	Training-Set	62.66	78.42	91.86	95.83
	Testing-Set 1	33.69	48.91	70.08	83.72
	Testing-Set 2	43.90	61.65	82.38	91.13

Table 1: The recognition rate when using non-linear estimation formula in Viterbi-decoding

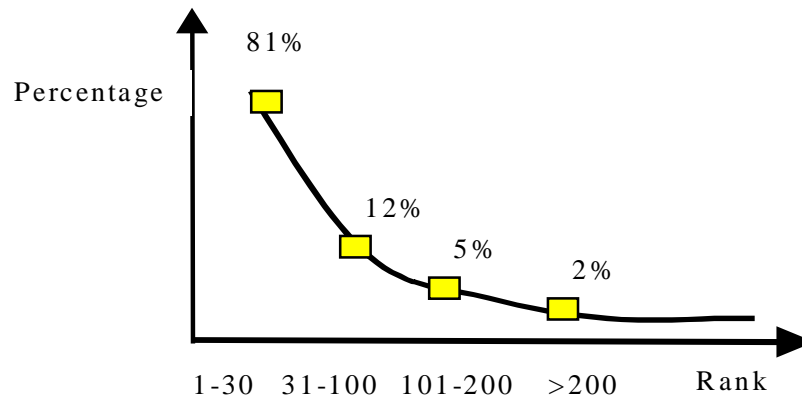


Figure 4: The effect of non-linear estimation

5.3. Comparison of FC HMM and THMM

The recognition rate of FC HMM is shown in Table 2, and also is that of THMM so we can compare them expediently. From which we can see that whether in Training-Set or Testing-Set recognition effect of FC HMM are both better than that of THMM. To Training-Set, the Top1 recognition rate of FC HMM is 6 percent higher than that of THMM. To Testing-Set 2, i.e. testing utterances of trained-speaker, FC HMM is 4 percent higher than THMM. To Testing-Set 1, i.e. utterances of untrained-speaker, FC HMM is 3 percent higher than THMM.

Comparing to BC HMM reported by S.Takahashi[9], FC HMM which characterizes frame correlation by using non-linear estimation formula contributes a little higher performance than BC HMM. For FC HMM does not bring any more memory complexity than THMM and it just brings a little more additional computing quantity than THMM so we can say FC HMM is an efficient method to model frame correlation in HMM.

Model	Recognition Set	Top 1	Top 2	Top 5	Top 10
HMM	Train-Set	59.93	76.29	90.12	95.05
	Test-Set 1	32.50	48.29	70.05	82.98
	Test-Set 2	41.22	58.96	80.47	89.88
FC- HMM	Train-Set	66.01	81.10	92.70	96.59
	Test-Set 1	35.78	51.53	72.02	84.42
	Test-Set 2	45.63	63.50	82.80	91.23

Table 2: The recognition rate of FC HMM

6. Conclusion

In this paper we present a novel method to incorporate temporal correlation into a speech recognition system based on traditional hidden Markov models (HMM's). At first, we use the joint conditional probability to represent frame correlation. Then, we use a non-linear probability estimation formula to characterize the correlation of adjacent frames. The methods reported before bring either a large increase of the model parameters or a lot of additional computing quantity. The FC HMM reported in this paper does not bring any more memory complexity and it just brings a little more additional computing quantity so we can say FC HMM is an efficient method to model frame correlation in HMM. Another advantage of the method is that it can be easily incorporated into HMM which we have already had. How to more precisely non-linear estimate the first-order forward frame correlation and how to use the method in high-order forward and backward frame correlation is needed to furthermore researching.

7. REFERENCES

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